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A review of aircraft auxiliary power unit faults, diagnostics and acoustic measurements

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A R T I C L E I N F O

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A B S T R A C T

The Auxiliary Power Unit (APU) is an integral part of an aircraft, providing electrical and pneumatic power to various on-board sub-systems. APU failure results in delay or cancellation of a flight, accompanied by the imposition of hefty fines from the regional authorities. Such inadvertent situations can be avoided by continuously monitoring the health of the system and reporting any incipient fault to the MRO (Maintenance Repair and Overhaul) organization. Generally, enablers for such health monitoring techniques are embedded during a product's design. However, a situation may arise where only the critical components are regularly monitored, and their status presented to the operator. In such cases, efforts can be made during service to incorporate additional health monitoring features using the already installed sensing mechanisms supplemented by maintenance data or by instrumenting the system with appropriate sensors. Due to the inherently critical nature of aircraft systems, it is necessary that instrumentation does not interfere with a system's performance and does not pose any safety concerns. One such method is to install non-intrusive vibroacoustic sensors such that the system integrity is maintained while maximizing system fault diagnostic knowledge. To start such an approach, an in-depth literature survey is necessary as this has not been previously reported in a consolidated manner. Therefore, this paper concentrates on auxiliary power units, their failure modes, maintenance strategies, fault diagnostic methodologies, and their acoustic signature. The recent trend in APU design and requirements, and the need for innovative fault diagnostics techniques and acoustic measurements for future aircraft, have also been summarized. Finally, the paper will highlight the shortcomings found during the survey, the challenges, and prospects, of utilizing sound as a source of diagnostics for aircraft auxiliary power units.

1. Background to the literature survey

In the current era, the world has no boundaries and people can travel across the globe within predetermined times. This has been achieved with modern aircraft with very mature levels of aircraft operations, maintenance, and component reliability. Like all other aircraft subsystems, the availability of the auxiliary power unit (APU) is of paramount importance to meet the desired operational demands in a timely manner. Regular maintenance ensures that the APU provides the desired performance and does not fail. Even if a failure occurs, diagnostic mechanisms are in place for the timely recovery of faulty equipment. Ultimately, a cost is associated with each segment of planned or unplanned maintenance activities. One way of reducing the cost is to automate the fault diagnostic process by deploying sensors that do not interfere with the aircraft functionality but are still able to acquire significant information about the system. Acoustic sensors fall into the category of such non-intrusive sensors, they can capture a wide range of information and assist in better fault diagnostics. The development of such diagnostic systems can expedite the recovery process, reduce the person-hours consumed during troubleshooting, provide accurate fault classification by excluding human interaction from the troubleshooting loop, and eventually reduce aircraft downtime.

To enable the above-mentioned approach, a comprehensive literature review was necessary to re-evaluate the work done by the research community in the appropriate domains. This led to the compilation of this review article, which aims to cover all the relevant domains needed to be understood before proceeding towards the development of an acoustics-based fault diagnostic framework for an aircraft APU. The areas touched in this review are shown in Fig. 1. The major areas to be explored are shown as large circles. Section 2 will discuss APUs, their functions, fault modes, and currently adopted maintenance strategies. The section will also cover the technological advancements, made or suggested, for aircraft APUs. Section 3 will focus on all types of fault

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Nomenclature

ACARE	Advisory Council for Aeronautics Research in Europe
AFEWT	Adaptive Filtering Empirical Wavelet Transform
ANN	Artificial Neural Network
ANOPP	Aircraft Noise Prediction Program
ANTLE	Affordable, Near-Term Low Emissions
APU	Auxiliary Power Unit
BIT	Built-in Test
BP	Back Propagation
BPF	Blade Pass Frequency
BPM	Band-Pass Mesh
COTS	Commercial off-the-shelf
CWT	Continuous Wavelet Transform
DWT	Discrete Wavelet Transform
ECS	Environmental Control System
EEMD	Ensemble Empirical Mode Decomposition
EGT	Exhaust Gas Temperature
EPN	Effective Perceived Noise
EVNERT	Engine Validation of Noise and Emission Reduction Technology
EWT	Empirical Wavelet Transform
FAA	Federal Aviation Administration
FADEC	Full Authority Digital Engine Control
FFT	Fast Fourier Transform
FMEA	Failure Modes and Effects Analysis
FTIR	Fourier Transform Infrared
GLCM	Gray Level Cooccurrence Matrix
GPA	Gas Path Analysis
GPU	Ground Power Unit
IATA	International Air Transport Association
ICE	Internal Combustion Engine
IHHT	Improved Hilbert–Huang Transformation
IMF	Intrinsic Mode Function
IVHM	Integrated Vehicle Health Management
KDEMI	Kernel Density Estimator Mutual Information
LPC	Linear predictive coding
LRU	Line Replaceable Unit
MED	Minimum Entropy Deconvolution
MES	Main Engine Start
MI	Mutual Information
MRO	Maintenance Repair and Overhaul
MW	Megawatt
NAH	Nearfield Acoustic Holography
NG	Next Generation
OASPL	Overall Sound Pressure Level
OEM	Original Equipment Manufacturer
PCA	Principal component analysis
PDF	Probability Density Function
PSD	Power Spectral Density
RMS	Root Mean Square
ROC	receiver operating characteristic
RPM	Revolutions per minute
RUL	Remaining Useful Life
SAE	Society of Automotive Engineers
SOFC	Solid Oxide Fuel Cell
SPL	Sound Pressure Level
STFT	Short-Time Fourier Transform
STOL	Short Take-Off and Landing
SVM	Support-Vector Machine
TEENI	Turboshaft Engine Exhaust Noise Identification
TKEO	Teager-Kaiser Energy Operator
TSA	Time Synchronous Averaging
VTOL	Vertical Take-off and Landing
WPT	Wavelet Packet Transform
WVD	Wigner-Ville Distribution
ZCR	Zero-Crossing Rate

diagnostic methodologies explored by the research community. Some of the challenges associated with emerging technologies will also be discussed. Section 4 is dedicated towards understanding various aspects of gas turbine noise, and the kind of experiments performed for its characterization. State-of-the-art methods for noise reduction in novel/future aircraft will also be presented. The last section (Section 5) is built on the information gathered from the previous sections and summarizes the research gaps, opportunities, and challenges involved when dealing with acoustics for engine health monitoring or fault diagnostics.

2. Aircraft auxiliary power unit

Auxiliary Power Units are turboshaft engines mounted on an aircraft for fulfilling electrical and pneumatic needs for any given aircraft. Table-1 provides information about APU usage during various phases of flight or ground operations [1]. APUs are primarily used when the aircraft is on the ground and a Ground Power Unit (GPU) is not available. Emergency power may also be delivered by the APU in case of main engine failure during flight. The idea behind integrating APUs into aircraft is to inhibit the use of main engines during ground operations to save fuel and to reduce emissions as well.

2.1. APU functions

Unlike aircraft main engines which are primarily responsible for generating thrust, APUs are designed to generate shaft power which is generally used to drive an electrical generator. In addition to electrical power, the APU provides bleed air which is either taken from one of the compressor stages or a designated load compressor is designed for this purpose. This compressed air is required by the aircraft's Environmental Control System (ECS) which provides air conditioning and pressurized air to the cabin. The bleed air from the APU also drives the main engine's air turbine starter during startup. This excludes the need for a heavy and big electrical component for achieving the same purpose. Depending on the aircraft design, APUs may also be used to deliver compressed air to the wing anti-ice system to prevent the formation of ice due to atmospheric conditions. Unlike the main engines, APUs are designed to operate at lower altitudes as per the operational requirements. Another important characteristic of the APU is the handling of electrical and pneumatic load at the same time and the prioritization which takes place if an overloading condition is sensed.

Like any other aircraft system, APUs are desired to be fuel-efficient, light in weight, occupy minimum space, contribute less towards aircraft noise, and should be easy to maintain and operate [2]. APU usage can range from mere 25 min for passenger aircraft to several hours for cargo aircraft [3] at airports where Ground Power Units are not available. Generally, it is desirable to limit the use of APUs because they generate more noise as compared to their counterparts. Some airports put restrictions on the use of APU to minimize environmental effects. Depending on the required electrical and pneumatic power for each aircraft, manufacturers have developed a range of APUs based on similar technologies. There is a wide range of APUs (mostly from the same manufacturer) that have been in service for various categories of aircraft [4]. In some cases, the same model of APU is installed on different types of aircraft due to similar power requirements.

Auxiliary Power Unit is designed to operate with minimal effort from the aircraft operator so that the pilot can focus on primary tasks. Therefore, an electronic control unit (analog or digital) continuously monitors and regulates the operation of the APU. Some of the parameters being monitored are shaft speed, EGT, Oil temperature, differential pressures, and generator output. In response to the state of APU, the control unit modifies the fuel flow to keep the operation within desired limits. A complimentary surge control system is also part of the feedback system, which inhibits surge conditions for safe operation. Most critical parameters are displayed in the cockpit and the pilot has the option to react to a hazardous condition like fire.

2.2. APU maintenance

Overall costs associated with an aircraft APU are pictorially represented in Fig. 2. Maintenance is one of the main cost drivers for operating aircraft APU. Failure of an APU in air or ground results in cancellation or delay in flight departure, which inhibits flight operations. An aircraft APU that requires maintenance after 7000 flight hours, would require a maintenance cost of nearly $0.4 Million [4]. In case of failure, costs are associated with its removal, disassembly, repair, and replacement. As per FAA's Service Difficulty Reporting database, aircraft APUs are found to be replaced more than 50% of the time whenever a fault is reported. Aviation Week in its Biennial survey reported that the world fleet needed over $4 Billion for MRO of all APUs in 2018.

Table 1
Typical usage of aircraft APUs [1].

Phase of Flight	APU Usage	Usage frequency
Ground operation	Environmental control system (ECS) Main Engine Start AC Power (400 Hz)	Mostly
Taxi-out	Backup power	Sometimes
Taxi-in	Backup power for large aircraft	Sometimes
Take-off	Backup power	Sometimes
Landing	Nil	Mostly
In-Flight	Electrical & Pneumatic Power	In Emergencies

Apart from the costs associated with unscheduled maintenance itself, regulatory authorities may also impose hefty fines if a scheduled flight is canceled or delayed for more than a certain time limit. The fine comes in the form of compensation which must be paid to each boarding entitled passenger or the airlines may be asked to pay for lodging costs of a passenger. As per European Union Flight Compensation Regulation 261/2004 [5], the compensation amount depends on the distance to be traveled by the scheduled flight and it can be €600 per passenger.

An aircraft is a complex combination of several sub-systems and APU is one of them. APU has equal importance like any other system on the aircraft because it provides electrical and pneumatic power when the

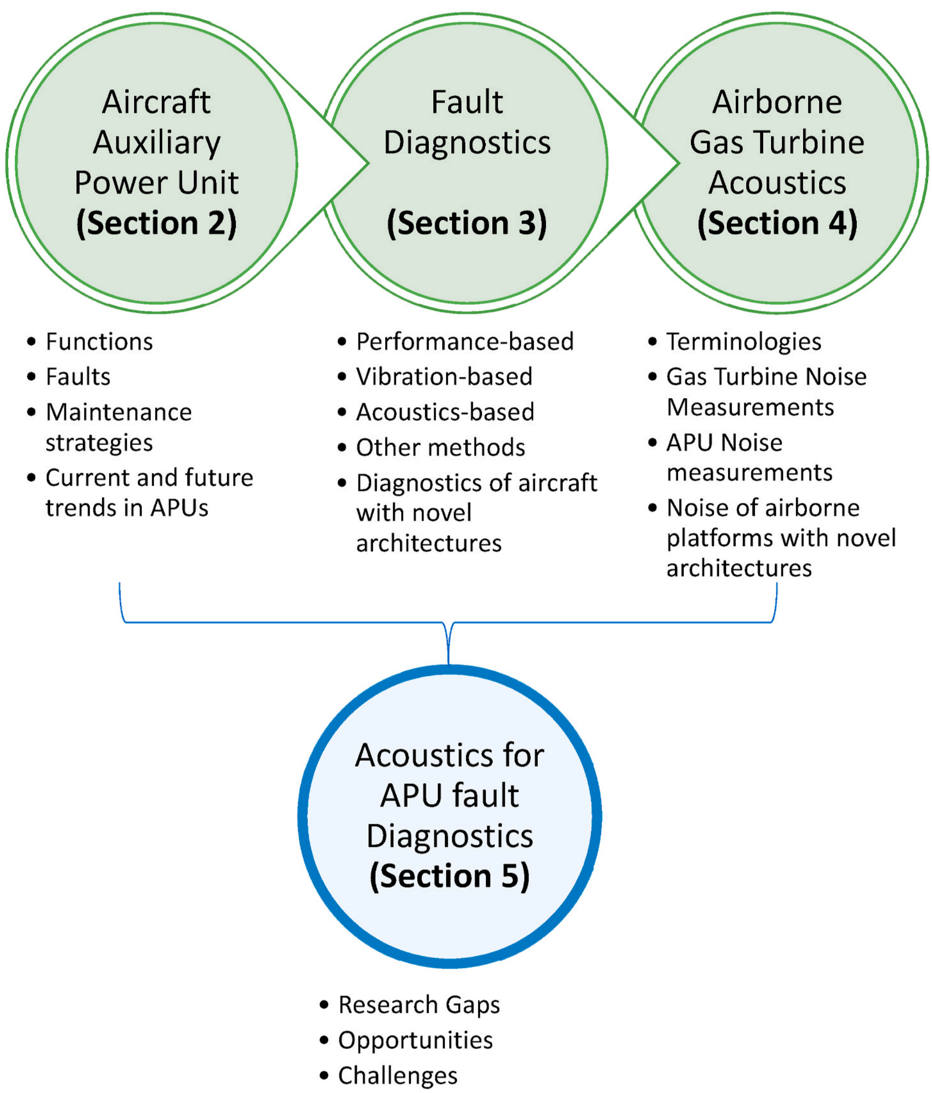

Fig. 1. Areas covered through the literature survey.

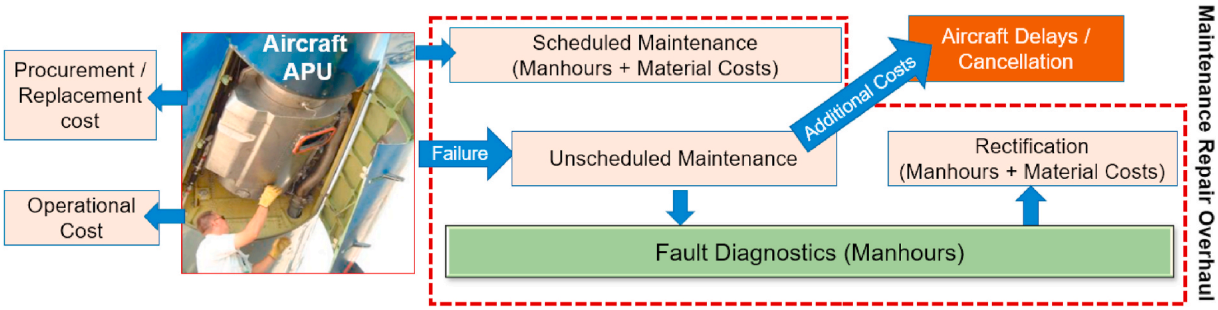

Fig. 2. Costs associated with aircraft APU.

main engines are not operating on the ground. Furthermore, in case of main engine failure, the aircraft is designed to acquire power from APU. Therefore, APU should be reliable and regularly maintained to meet the desired performance and failure-free operation. However, if a failure does occur, they result in in-flight emergencies which can lead to turn-around or diversions. In a study conducted on power plant-related occurrences between 2008 and 2012, APU failures were found to occur second most frequently after abnormal engine indications [6]. The study also shows that APUs are generally placed in the power plant category and assessed together with the main aircraft engines and are therefore an important part of an aircraft.

2.2.1. APU failure mechanisms

Several studies have been conducted on various failing mechanisms of aircraft APU. Validation of the Weibull model using APU oil pump failure data has been done [7] and correspondingly recommendations have been made for the optimum time for their replacement. In the study by Ref. [8], it was concluded that one of the reasons for APU failure is an uneven distribution of fuel from the nozzle which leads to wear of turbine disk. An independent study has been conducted on cracks in the APU exhaust duct which is a hazard to the structural integrity of the aircraft [9]. Potential causes of rotor seizure in 737 APU are discussed in Ref. [10] and the fault has been attributed to be initiated due to foreign object damage to compressor stage or a bearing fault. As per [4], failure of APU rotating parts result in high EGT, high oil consumption, and low power outputs. In Ref. [11], APU failure results have been categorized into two groups; those which can be fixed on-wing by replacing faulty Line Replaceable Units (LRU) and those which require APU removal accompanied with complex maintenance actions. The on-wing faults are rectified quickly because the LRUs are placed at convenient locations as per the design-for-maintenance approach. In the case of APU removal and visit to repair shops, the cost of material mainly contributes to the overall amount, whereas the costs associated with the manhours are between 20% and 30% [4].

In [12], it is stated that 30% of gas turbine failures are due to turbine blade failures. These occur due to blade corrosion and erosion, hot start, compressor fouling, and operating the engine beyond its limits [13]. describes the interdependency which exists between components failures for an APU. An example of this type of interaction is provided which describes how turbine blade tip loss induces rotor unbalance, which eventually results in bearing failure. A summary of failure modes and their frequency of occurrence is also provided which shows that the turbine is more prone to failures than any other components in the APU power section [16]. A similar frequency of turbine blade failures is also reported in Ref. [14].

Detailed analysis of APU component failures was done in Ref. [15] to update the OEM-provided FMEA parameters. For this purpose, the OEM FMEA list and maintenance data were obtained, by the authors, from the airline operator for subsequent analysis. During the study, which was focused on the inability to start failure, dissimilarity was observed when field data was compared to OEM data. As per the maintenance data, startup failure occurs due to failure in starter, igniter, fuel control assembly, fuel pump, fuel flow divider, low oil pressure switch, speed sensor, and thermocouple. The rank of each component had to be updated because they deviated substantially from the OEM provided ranks. The study concluded that it is difficult for the product designers to accurately determine failure(s) and their probabilities before the product has made it into service. Therefore, it would be advisable to re-evaluate the OEM-provided parameters using operational and maintenance data after sufficient data has been collected.

Other than the published literature, the Federal Aviation Administration's Service Difficulty Reporting database provides useful information about aircraft systems' failures (including APUs). The database contains defect reports submitted by airline operators starting from the year 1993 and these reports can be publicly accessed by using FAA's website. As per the database, APU reported defects continue to rise in the last few years with the highest number recorded in 2018 (Fig. 3). Moreover, such instances have led to in-flight emergencies more than one hundred times during the last three decades.

Further scrutiny of the extracted information from the FAA's repository gives considerable insight into the causes/nature of APU failures and the type of decision that is generally taken after fault diagnostics. Meaningful information has been gathered by searching for a combination of various keywords in the discrepancy column. It is found that the APUs are replaced more than 50% of the time whenever a defect/failure is reported. Fig. 4 depicts the various kinds of defects/failures which have been reported by the airline operators and the maintenance personnel. The main problems associated with APUs are smoke/smell from the bleed system and unwanted shutdowns. The figure also puts together potential causes that lead to such failure conditions. It is to be noted that the root cause of a failure is not generally diagnosed at the first line of maintenance. Hence, a detailed level of information about the potential causes and their effects could not be gathered from the given defect reports. It is further observed that the underlying causes and the faults do not generally occur independently. Most of the time, multiple faults occur simultaneously and cannot be treated as mutually exclusive events. For instance, an APU warning light may appear in the cockpit which may or may not lead to APU shutdown, generator failure, or unwanted vibrations.

2.2.2. Maintenance strategies for aircraft APUs

Mechanical systems can range from small electric motors to huge turbomachines depending on the kind of output that is desired from them. In certain applications, the equipment could be producing Megawatts of energy and the components constituting these machines would be subjected to extreme pressures, temperatures, loads, and stresses. If there are no systems in place for monitoring and reporting the apparent and incipient failures, then the outcome could be catastrophic. Owing to the severity of the situation, hazardous and safety-critical systems are equipped with sensors and associated hardware, which ensure that the system is operating within safe limits. Moreover, maintenance practices are in place to avoid accidents, ensure desired performance and system availability. The approaches range from preventive maintenance schemes to condition-based maintenance. The

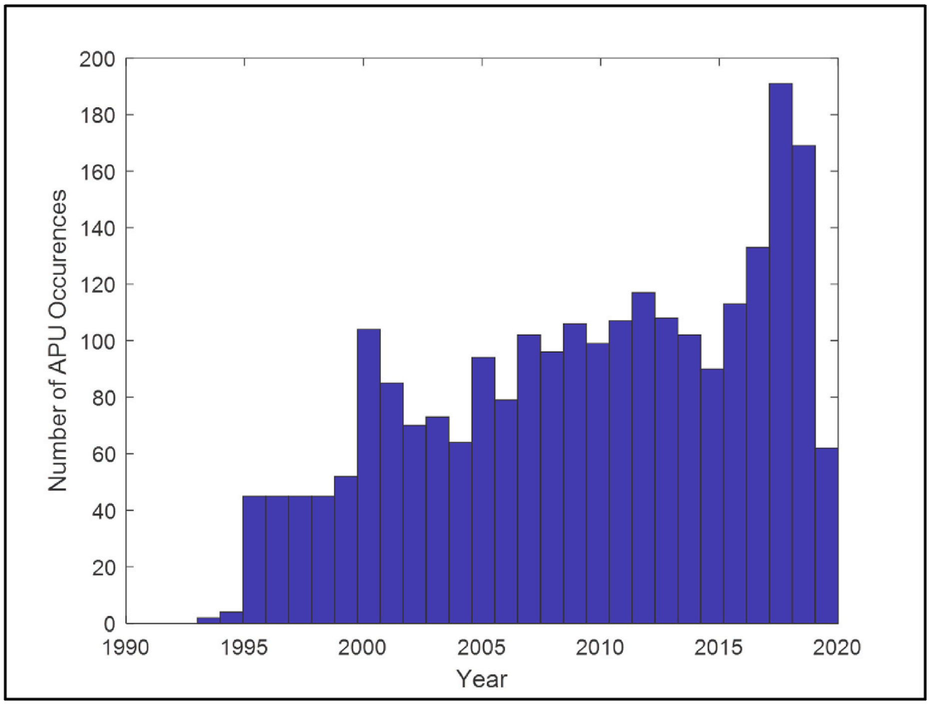

Fig. 3. APU faults histogram.

Cause	%
FOD	4.25
Overservice / Excess oil	2.00
Low oil quantity	1.75
Seal Fail	1.62
Bearing / Gear Fault	0.67
Blade Damage	0.58
Surge Valve Fail	0.37
Wiring Damage	0.33

Intermediate Effect	%
Fuel / Oil Leak	17.65
High Oil Consumption	1.33
Low oil pressure	1.25
Making Metal	1.21
High EGT	0.46
Seizure	0.37
High Oil Temperature	0.33
Surge Condition	0.29

Final Effect	%
Smoke / Smell	61.70
APU Shutdown / Fail	34.26
Startup failure	9.24
Fire	9.12
Vibration / Noise	4.62
Warnings	3.25
Generator Fail	0.92
Catastrophic Failure	0.25

Fig. 4. Causes and effects of APU failure.

latter technique is an emerging field of research with huge potential in the industry because it addresses the key questions of maintenance engineers and eventually leads to decreased downtimes.

A range of maintenance strategies is adopted to keep APUs operational and avoid unnecessary downtimes. As per the study conducted on the 737-NG [8], APUs are initially subjected to mandatory scheduled maintenance practices which span from visual inspection and component replacement when the APU is in the aircraft to removal and installation of life-limited parts at the shop level. This activity is conducted at regular intervals regardless of the condition of the component (s) rendering the effort unnecessary in certain cases. However, even with the preventive maintenance strategies, an unexpected fault may appear in the system, and depending on the nature and severity of the fault, it must undergo unscheduled maintenance with added operational disruption costs.

In contrast to the above, a desirable way is to execute condition-based maintenance, which eliminates the need for resorting to unnecessary maintenance efforts. This is achieved by using condition monitoring data and failure prognostics models [16] materialized using data-driven or physics-based approaches. The former approach makes use of aircraft operation and maintenance data while the latter one generally relies on gas path analysis. However [17], maintains that the airlines generally follow regular maintenance for APU, and they are not repaired until a failure occurs. Operating APU under such sub-health conditions can have undesirable economic and safety impacts, which must be mitigated using prognostics and health management strategies. The researchers who proposed failure prediction of aircraft APU relied greatly on its operational, maintenance, and repair data. For example [18], utilized failure and performance data from over fifty APUs to develop a Weibull-based method which is shown to perform well in predicting APU failure rates.

2.3. Current and future trends in APUs

A study on the importance of APUs is reported in Ref. [19], in which the potential advantages of removing APU from the existing aircraft are discussed. The study concluded with the finding that removing APU from aircraft can provide some economic and ecological benefits, only if those aircraft are operated for long ranges. Similarly, a detailed study has been reported in Ref. [20], which highlights the benefits of replacing fuel-powered systems (like APU/GPU) with hydrogen-solar-based energy networks for airport and aircraft electrification. The study shows that, although the upfront costs would be inhibitive, the energy costs and emissions can potentially be significantly reduced. Possible elimination of APUs from an electric aircraft is investigated in Ref. [21]. This is because the power for this kind of aircraft will be solely provided by technologically advanced batteries with a very high level of specific energy. However, at present, only short-range missions are possible with the less-advanced batteries. On a smaller scale [22], investigates the possibility of using low-voltage power sources as a source of power for the aircraft's electrical needs. The proposed solution is said to provide voltage regulation and is robust against load fluctuations.

Numerous studies have been conducted which assess the shortcomings in the current APU design and suggest ways of improvement. In this regard [23], presents a high-performance motor controller design for the starting system of an aircraft APU, that eliminates the need for a dedicated battery, the DC starter, and the clutch assembly. The effects of impulse load on an aircraft electric system are studied in Ref. [24] and the suggested modifications are made which will ensure that the APU or main engine's generator can withstand such loads. The study concludes that real-time compensating devices and a supervisory control system are necessary to maintain the electrical system's stability [25]. adopted Non-dominated Sorting Genetic Algorithm-II for choosing the parameters of a passive filter for an APU inverter. The response of the designed filter proved to be superior to the standard filters [26]. looked at the possibility of optimizing the rotor design of an aircraft APU. The proposed method considered the rotor weight, the maximum unbalance response, and the response during the aircraft maneuvering phase for optimization. A Hybrid genetic algorithm was used for three-objective optimization, which resulted in a better design as compared to a reference APU. A design of a multi-level inverter for aircraft APUs is presented by Ref. [27], which comprises a smaller number of components and therefore is smaller in size and cost-effective. Development of an Auto Transformer Rectifier Unit for an aircraft APU is also needed to control the dc-powered electric motors when shifting towards a more electric design [28].

As the aircraft is becoming more electric, the need for electric systems is increasing, which would replace the existing hydraulic and pneumatic systems [29]. presents a novel design for an aircraft starter/generator system that allows electrical motoring of the aircraft engines. The developed system can start the aircraft engines through electrical power and therefore pneumatic power from the APUs would no longer be required. The benefits of a bleed-less architecture are discussed in Ref. [30]. The study reports that an APU designed for an aircraft with bleed-less architecture can save fuel up to 50 kg/h for a 50-passenger aircraft.

Possible utilization of APU for futuristic and more electric aircraft will be of providing power to the electric motors that will drive the wheels of the aircraft [31,32]. This capability would allow the main engines to remain off during the taxi phase, but it would increase the aircraft mass due to the presence of motors. The solution has also been tested through taxi trials of an Airbus A320 aircraft, which showed a reduction in fuel by 3% [33]. The current battery technologies do not provide the energy density for energizing a fully electric short-haul aircraft. However, the possibility of improving the existing APUs to provide higher levels of electrical energy is there [34]. There have been attempts of replacing BA-146 engines with electric motors and powering them with the electrical power generated by a Rolls-Royce AE 2100 APU. Furthermore, the predicted power density for future aircraft is expected to reach 40kVA/kg. The key enablers for this type of power would constitute non-conventional technologies like superconductivity. Some devices have already been developed with a power density of 16kVA/kg. While designing a more-electric aircraft [35], emphasizes the need for upgrading the APU generators to meet the desired electrical demands.

The researchers have been proposing innovative ideas to fulfill the requirements for an aircraft's auxiliary power needs. In Ref. [36], a novel design of an ICE engine is proposed that can find its application as an aircraft APU. The engine has no reciprocating components and hence has vibration-free characteristics. The invention's configuration, geometry, and operation are explained, and a prototype is built which has shown to achieve the desired outcomes under no-ignition conditions by driving it using an electric motor. The concept is in the early stages and has yet to satisfy all the criteria needed for an airborne application. Similarly, the feasibility of using the heat generated by a helicopter as a source of auxiliary power using the Organic Rankine Cycle has been carried out by Ref. [37]. However, the results showed that the power generated by this scheme was very reduced and thus this approach is not practically possible.

Lastly, there is a plethora of information available in the public domain literature which revolves around the possibilities of using fuel cells for airborne applications. In Ref. [38], an in-depth review is carried out on the existing SOFC technologies that can potentially replace conventional APUs. A symmetrical and planar SOFC design is studied by Ref. [39]. [40] designed a hybrid Fuel Cell/battery-based design for 767 as a replacement to APU. In Ref. [41], the key benefits of using SOFC-based APU are evaluated by simulating the performance of the fuel cell using proprietary library modules. The study employs a twin-engine aircraft designed for short-range missions. The simulation compares the performance of SOFC-based APU with a conventional gas-turbine-based APU and it is found that the former design performs better in terms of efficiency and fuel reduction. However, it is asserted that the findings are at a conceptual level and various aspects of safety and integration have to be considered before making it practical. The preliminary design of a fuel-cell-based aircraft is reported and the design is also tested on a 2-seater aircraft first time [42]. IATA, while considering the possible technological advancements needed to reduce fuel consumption, hints at the incorporation of fuel cells as a replacement to conventional APUs is also under consideration [28]. However, it is asserted that hydrogen generation is currently not sufficient, and infrastructure is required to be developed on a global level for hydrogen generation.

3. Fault diagnostics

For any given machine, maintenance strategy is incomplete without a comprehensive fault diagnostics method. Diagnostics aims to correctly identify faults that generally lead to warnings, performance degradation, and unsafe operation. Ideally, modern diagnostics methods should be all-encompassing and inherently possess the attributes mentioned in Table- 2 (gathered from Refs. [43,44]). For any given system, the manufacturer or designer selects the optimum diagnostics method which can provide the maximum information about the system at the least possible costs and efforts.

Multiple types of diagnostics methods have been explored by the research community and most of them are in use by the industry. Any given type of diagnostics method can be uniquely identified by the adopted methodology and the type of capabilities it possesses. These are:

(a) Type of fault(s) it can identify
(b) Nature of sensing mechanism
(c) Number of sensors employed
(d) Signal Processing technique applied
(e) Machine Learning algorithm used

Table 2
Features of a good fault diagnostic method.

Desirable attribute	Enabling features
Accurate	Exact amount of deterioration in the correct component
Low cost	Simple
	Low implementation cost
	Small number of sensors
Reliable	High probability of detection
	No False alarm
	Fail-safe
Quick	Online detection capability
Comprehensive	Able to detect multiple faults simultaneously
	Able to detect all possible faults

(f) Data/information fusion methodology
(g) Performance of diagnostics method in terms of accuracy
(h) Real-time/Offline capability
(i) Ability to detect and identify faults during transient or steady-state

After decades of research, a considerable number of fault diagnostics methods have surfaced, each being capable of identifying a certain number of degraded or faulty components in a machine. Each method requires a unique sensor-set and a series of algorithms to convert the sensor data into useful information about machine conditions and fault locations. In the subsequent paragraphs, machine fault diagnostics methodologies are explained in detail, which have been categorized primarily based on the type of sensor used for processing.

3.1. A rudimentary form of fault diagnostics

Aircraft engines, including APUs, are complex systems, which require continuous monitoring for flight safety and timely maintenance. This may be achieved through the display of vital information through cockpit displays (engine RPM, EGT, oil quantity, oil temperature, etc.) [45]. Moreover, modern APUs are driven by a dedicated FADEC for feedback and control of the engine under various conditions. FADEC regulates fuel supply to meet desired performance, prevents compressor surge, initiate automatic shutdown in case of failure and record historical data into memory. FADEC also performs a built-in test (BIT) during startup and continuous operation. The outcome of the test is based on status monitoring of sensors and actuators based on electrical signals. BIT fails if FADEC's connection with the component is found to be either open or short-circuited. Moreover, a failure is also detected if sensor data falls into an invalid range. Generally, BIT does not trigger a failure if the sensor data is noisy or biased or if the failure condition is momentary. In case a safety-critical failure is detected, FADEC initiates APU shutdown and records the information in memory for diagnostics purposes.

The seemingly decent approach mentioned in the previous paragraph does not help in diagnosing the complete range of failures that can occur in the system and are difficult to identify due to the intricately integrated nature of a gas turbine. Consequently, manufacturers must provide troubleshooting techniques through which the maintenance engineers have to traverse to single out the potential cause(s) of failure (s). Depending on the type and nature of failure, this process can be time-consuming and result in unwanted delays.

3.2. Performance-based diagnostics

Performance-based analysis of gas turbines is a prevalent approach towards engine health monitoring. The idea is to monitor measured variables such as temperature, pressure, and rotational speeds and relate them to engine health variables that are not directly measurable (like efficiency). Implementation of this approach requires an in-depth understanding of engine dynamics and the possible development of a digital twin. This will be accompanied by the selection and installation of correct types of sensors with added signal processing techniques for noise removal. In cases where sensor coverage is limited, various approaches like Kalman Filter and optimization/combinatorial techniques are proposed in the literature [46].

Performance-based monitoring (also called gas-path analysis) techniques give considerable insight into the degradation levels of compressors and turbines of a gas turbine [47]. The degradation could be the result of fouling, erosion, corrosion, or tip clearance. Aircraft engines, compared to industrial engines, are more susceptible to fouling because they do not have an air filtration system. However, this statement needs further assessment because in modern turbofan engines with a high bypass ratio, the particles are separated at the fan as they are pushed outwards due to centrifugal forces acting on them. On the other hand, erosion in aviation is a frequently occurring phenomenon that greatly affects those engine components that are directly in contact with the atmosphere [48]. Numerous particles in the air deteriorate the component surfaces and lead to cracks and weight loss of the material. Nevertheless, the effect of degradation is the same regardless of the type and nature of the gas turbine. It is also highlighted that implementation of performance-based diagnostics and prognostics is a challenging task because it requires an in-depth understanding of the engine performance with inherent non-linearities and an elaborate set of sensor data that may be corrupted by noise and bias. Even in the presence of these complexities, performance-based health monitoring of gas turbines is considered a faster and reliable way of acquiring information and using it for maintenance.

Considerable importance is given to evaluating the degradation of compressors and turbines because they are the most expensive parts of an engine. Therefore [49], discussed the cause and effect of compressor fouling and how it can be detected using performance deterioration. In the case of a combustor, it is stated that its performance deteriorates when carbon deposits start breaking off from the nozzles, and soot is produced as a result of incomplete fuel burning.

A practical realization of the model-based diagnostics approach has been presented in detail in Ref. [50], in which a turbofan engine is subjected to multiple faults, and data is collected in healthy and faulty states for model development, testing, and validation. Only those faults were selected and implemented which could not damage the engines. The model was eventually shown to accurately determine the cause of failure, however, the results were reliable during steady-state only.

3.3. Vibration-based diagnostics

Gas turbines, like rotatory machines, comprise mechanical components like bearings, rotors, and gears. Failures associated with these are rotor imbalance/misalignment, cracks, shaft rub, mechanical looseness, gear crack, gear tooth break, and defect in inner/outer race of bearing. Due to the mechanical nature of these faults, vibrations are induced which can be picked up by appropriate sensors. In certain cases, mechanical and performance-based (or aerodynamic) faults may be coupled (like engine surge/corroded blades) which results in excessive vibrations. For each type of failure in rotating machines, vibration frequencies are associated with them [51], and vibration techniques aim to look for the presence of these emerging frequencies under the presence of background noise that relates to incipient failures. Vibration measurement can be in the form of displacement/velocity probes or accelerometers and the sensors are generally placed close to bearings, gearbox, engine shaft, and engine casing [44].

A two-step knowledge-based system for turbomachinery vibration diagnostics is proposed in Ref. [52], in which certainty factor is used to express the relationship between symptom and cause. The usefulness of fuzzy-based analysis of machine data for diagnostics has been presented in Ref. [53]. Fuzzy logic allows flexible threshold levels since the vibration amplitudes cannot have the same implications for the complete range of similar machines.

3.3.1. Gearbox fault diagnostics

Numerous studies have been performed on gearbox faults diagnostics alone. They are either based on data collected from test rigs operated in a controlled environment or from actual systems. This field has matured to an extent that there are metrics associated with gearbox deterioration. These metrics are in the form of features that are more stable as compared to raw data and help in data reduction as well. A survey was conducted by Ref. [54] on these features, who then classified them into 5 different categories (Table- 3). The segregation is based on the type of pre-processing which is to be performed before calculating the features themselves. The categories start from virtually no pre-processing and end on a complicated approach in which Time Synchronous Averaging and band-pass filtering must be applied before the actual features are computed.

In an older study [55], reviewed the vibration-based health and usage monitoring techniques developed for a helicopter. It included techniques like DWTs, STFT, Analog/Digital Neural Networks, neuro-fuzzy algorithms, WVD, and gear condition monitoring metrics like FM0, FM4, NA4, NA4*, NB4, and ND48*. The reviewer made greater emphasis on introducing the methods instead of comparing their results.

In [56], de-noising of weak fault signals was performed using the Donoho method with Morlet wavelet with a generalized soft-thresholding feature. Morlet mother wavelet was selected because it resembles an impulse that is generally produced in bearing and gearbox faults. The shape of the Morlet Wavelet can be optimally controlled using the minimal entropy method. The combination of Hilbert and wavelet packet transform was proposed for extracting modulating signals for detecting an early gear fault [57]. The results were analyzed using simulated and real signals and it was found that the method was able to handle the time-varying situation and had better accuracy and efficiency as compared to WPT (wavelet packet transform alone). The resulting transform was visually inspecting for locating faults.

Improved HHT (iHHT) is also a method for machine fault diagnostics [58]. This method is HHT applied on sensitive IMFs calculated from the EEMD of the vibration signal. Comparison between time and frequency domain features for gear crack diagnostics is also available in Ref. [59]. Denoising of gear crack signal using Wavelet Transform with Gabor Wavelet has also been evaluated, where the threshold was selected using median absolute value [60].

Joint Time Frequency Analysis on vibration data is suggested for health monitoring of engine accessories like reduction gearbox [61]. A very robust method for gear crack de-noising is proposed using biorthogonal wavelet transform [62]. The method can identify gear damage at the level of an individual tooth. In the review by Ref. [63], it is stated that the vibration data varies with varying load and the only reliable data that can be captured is under no-load conditions. However, even under such circumstances, teeth lose contact and lead to random vibrations. While summarizing the effect of gear faults on the amplitude and frequency modulation [63], wrote that shaft misalignment and eccentric gear lead to amplitude modulation, whereas local gear failure effect frequency modulation due to speed variation. In Ref. [64], possible locations of vibration sensors on a gas turbine are stated and the effect of compressor, combustor, and turbine failures on vibrations and performance parameters is summarized. However, only qualitative criteria for fault diagnostics are presented which may be insufficient for fault localization.

Machine rotor faults have been comprehensively studied using the physics-based approach and its validation using data collected from a Machine Fault Simulator [65,66]. Efforts have been made to localize unbalance faults using vibration data collected from the simulator. Autoencoder technique is yet another way for system modeling and analyzing discrepancy signal for gear diagnostics under varying load [67]. Adaptive morphological gradient lifting wavelet has also been applied for de-noising of signal and applying FFT to visualize the sidebands [68].

A recommendation is made in Ref. [69] to use Mel Cepstrum on vibration and acoustic data for diagnosing faults in a jet engine. During this study, a jet engine was operated under healthy and 02 faulty states to acquire vibroacoustic data and use it to model the fault classification algorithm. A time-domain technique is to use Dynamic Time Warping to generate a residual signal from raw and reference gear mesh signals and applied correlated kurtosis for diagnosing gear spalling [70]. Adaptive spectral kurtosis for denoising (extracting transients signals) using Morlet wavelet is another way of observing the transients in case of broken teeth gear [71]. In Ref. [14], RMS values of vibration are predicted based on a data-driven approach where data is collected from a 25 MW gas turbine at multiple instances for a span of 1 year. The developed ANN model is s Multi-layer perceptron-based and is shown to accurately predict vibration rates from known parameters. Sensitivity analysis of the input parameters reveals that the vibration rates are more sensitive to differential pressure across bearing, fuel consumption and rotor speed. The study was concluded without further analysis and a physical explanation of the results. A comprehensive review of time, frequency, and time-frequency domain condition indicators for gearbox fault detection is presented in Ref. [72].

Hilbert transform along with Wavelet packet transform has also been applied for localizing faults in the two-stage gearbox which was not possible using Wavelet Packet transform alone. The induced failures were gear pitting, chipped gear tooth, and spall on bearing outer race [73]. Similarly, [202] applied the Wavelet Bicoherence technique on vibration signals for diagnosing gear faults. TSA was done using up-sampled signal and mesh frequencies were removed before applying Wavelet transform. Finally, Wavelet Bicoherence processing was done, and Fisher Criteria was applied as a diagnostic feature [74]. proposes using spectral Kurtosis with envelope analysis for diagnosing bearing faults in wind turbine gearbox.

In [75], an explanation is made towards successful implementation of vibration monitoring which helped maintenance engineers in diagnosing failure in one of the bearings of a gas turbine using time-domain analysis. A model has been successfully developed for predicting the vibration behavior of gas turbines using the Neural Network approach [76]. In this approach, the state of the gas turbine is used as input to the model which predicts axial and radial vibration of the rotor. This information is compared with measured vibration data for diagnostics purposes. In another report [77], problems encountered during the vibration-based approach in gas turbines are discussed. It is stated that the desired health monitoring estimates from vibrations analysis are difficult to retrieve because they are masked by comparatively high levels of oscillations from the flow of air and combustion products. The situation is further deteriorated due to harmonics from various other sources as well; impellers, rotors, generators, gears, and other auxiliary accessories. A suggested way for diagnostics, which may not be practical in most cases, is to decouple the component(s) under study from the main engine and rotate in using an external drive.

3.3.2. Bearing fault diagnostics

Bearing faults have also been the object of study by the research community due to their significance in safe and reliable operations of turbomachinery. Resonance demodulation method for indicating gear tooth fault has been proposed in Ref. [78]. The method involves the removal of meshing harmonic frequencies and filtering the signal around structural resonance and employing Kurtosis as a fault indicator. The method was tested on numerically simulated data, test-rig data, and helicopter data.

The use of STFT with marginal time integration for extracting features in a ball bearing is mentioned in Ref. [79]. In Ref. [80], it is exhibited that the diagnostic features are susceptible to load conditions for ball bearings and have to be modeled as a function of load for better segregation of healthy and faulty data. Multi-fault diagnostics of simultaneously occurring gear and bearings faults can be performed using Hilbert Transform with Wavelet Multiresolution Transformation [81]. Cepstral pre-whitening on residual signal for detecting a fault in ball bearing has been recommended in Ref. [82]. Application of various signal processing algorithms like minimum entropy deconvolution (MED), Teager-Kaiser Energy Operator (TKEO) followed by Genetic algorithm, and kurtosis computation is discussed in Ref. [83] for bearing fault diagnostics using vibrational analysis.

A novel technique for helicopter bearings diagnostics is described in Refs. [84,85]. Usage of energy parameters of the multi-factor transfer function as a feature for fault detection is cited. This feature is computed from vibration signals, casing transfer function, bearing geometry, and rotation signal for onwards diagnostics. However, the experimental data was gathered in un-realistic conditions, since the engine was driven in ‘cold’ mode by a powerful electric motor. Feature vector computed from IMFs of vibration signals for diagnosing rotor and bearing faults has also received considerable attention [86]. It is claimed that adaptive filtering of EWT (Empirical wavelet transform) as a feature extraction tool produces better results for bearing fault diagnostics. It was followed by classification using a merger of KDE (kernel density estimator) and MI (mutual information). The method was termed AFEWT-KDEMI (Adaptive Filtering Empirical Wavelet Transform – Kernel Density Estimator Mutual Information) and was shown to perform better than SVM and BP techniques [87].

The combination of Adaptive Waveform decomposition for noise removal and Limper-Ziv Complexity as feature extraction method is another method of fault diagnostics [88]. An analytical model for pump bearing vibration using dimensional analysis is proposed and compared the results with experimental data for observing a trend in bearing deterioration [89]. The use of envelope spectrum of vibration signal and observed slice-spectrum for analyzing bearing faults is also mentioned [90]. Convolutional Neural Network with S-Transform for bearing fault detection is shown to outperform all other techniques [91]. For tacking distributed damages in bearings, a mathematical model has been developed for computing damage frequencies for the inner and outer ring of bearing. The model has also been successfully validated with experimental data [92]. Another feature extraction method is to compute the ratio of characteristic frequency computed from EEMD of vibration signal for bearing fault diagnostics [93].

It can be concluded that there is a lot of work that has been done in the field of fault diagnostics of rotating machinery using vibration data. The majority of the research has been towards fault detection and identification using test-rigs or a subset of the whole system, thus rendering the performance of developed algorithms to be contentious for a complete system. Since the component faults are studied separately, it is rare to see a detailed analysis of engine noise and its effect on components' characteristic frequencies. Moreover, selection and performance analysis of sensors of different types and specifications have not been made part of the research, which can be of great significance to the maintenance engineers who would be practically implementing the research.

3.4. Acoustics-based diagnostics

Several attempts have been made to harness the potential of utilizing airborne sound for health monitoring of rotating machinery. This is because microphones are easily installable as opposed to accelerometers since the latter require rigid connectivity to the component which is intended to be monitored. This is generally not feasible when the surface is not flat and is potentially at high temperatures. Although many commercially available accelerometers can sense machinery vibrations at higher temperatures, a considerable cost is associated with them. The whole activity of installing vibration sensors is suitable if they are being considered for condition monitoring when the product is in the infancy stage of development. However, the same process may not hold good if sensors are to be installed on vintage machinery or a certified product. Other than the reasons already mentioned, any mechanical modification to a product, once it is through from its design cycle, will entail risks, redesign, and costs.

Microphones belong to the category of non-intrusive sensors and they can capture a wide range of acoustic signatures emitted by mechanical components in the vicinity. Also, their installation would not require major alteration to machine structure. An astounding feature of acoustics is its capability of capturing variations in fluid flow characteristics which is not much pronounced in the case of vibration signals [94]. Nevertheless, the acoustics signals are proliferated by background noise, unwanted reflections, and reverberations which may cover the informative signal. This can, however, be evaded by using specialized signal processing techniques. Due to the inherent limitations, acoustics-based diagnostics has not received due attention and the studies that have been conducted are generally carried out in a controlled environment.

In [95], the effect of surface roughness on bearing noise was studied using microphones in an anechoic chamber and it was found that the produced noise has a proportional relationship with surface roughness. Smoothed pseudo Wigner-Ville distribution analysis of vibration and acoustic signals for gear faults diagnostics can achieve desirable results [96]. Moreover, it has been found that the acoustics-based technique performs better for detecting cracks. However, vibration signals can detect tooth defects at a much early stage. Comparison between vibration and acoustics signals is made using wavelet transform and it is concluded that acoustic signals can equally perform well in detecting faults in a gearbox. With regards to acoustic signals, they were found to be unaffected by small changes in position and orientation of the sensor [97].

Acoustic data can also be used to detect wearing and crack in gearbox by observing the trends in Power Spectral Density and Cepstrum results [98]. Comparison between the performance of using accelerometer, acoustic, and stator current data from an induction motor is made in Ref. [99]. It is concluded that the accelerometer signals outperformed the rest for diagnosing gear tooth wear if the Welch method is used for computing Welch Method. Near-field acoustic holography is a unique way of using acoustics for bearing fault diagnosis [100]. In this method, GLCM features are computed from NAH images and the optimal feature subset is selected based on F-score. The features are then used to train classifiers, and finally, diagnostics is done using multi-SVM. The results are promising but the dataset was collected in an anechoic chamber using several microphones. Empirical Mode Decomposition is a well-known technique that has been applied on vibration and acoustic data for fault diagnosis of ball bearing [101]. This method can also perform well in the absence of bearing specifications. Tests are conducted in a lab setup with healthy and fault-induced ball bearing. FFT is then applied to IMFs of the acoustic signal and it is found that bearing fault leads to increased intensity of computed frequency levels. The same method also allows the estimation of bearing frequencies.

In [102], it is stated the turbomachinery blade faults like blade rubbing can be captured by using acoustics. Diagnoses faults in planetary gears can also be done using acoustic signals and their frequency spectrum [103]. In one of the case studies [104], the usefulness of installing vibration and microphones on a vacuum pump is studied. It is shown that the two installed microphones can capture operational frequencies of the whole system even in the presence of background reflections. Comparison between vibration and sound signals shows that the microphones can capture spectral content which is sensed by the accelerometers also. The study has been conducted using low-cost sensors and no further analysis is performed.

Similar activity has been undertaken by Ref. [105], in which accelerometer and microphone are installed on a pump for studying bearing faults in a pump. Time domain, frequency domain, and envelope spectrum analysis are done, and it is shown that bearing frequencies' amplitude and harmonics are visible in the acoustics data and RMS values of acoustic envelope signals are robust features for performing fault diagnostics. Several other features and algorithms have also been computed using acoustic signals for detecting damage in rotary machines [106]. This includes Spectrogram, Wavelet Transform, co-occurrence matrix, and AdaBoost classification algorithm. Work on detecting gear misalignments using vibration and acoustic signals is also presented [107]. For this purpose, an experimental setup is developed for inducing gear-pair misalignments acquiring corresponding vibration and noise data under various operating conditions. Multiple techniques are employed for estimating misalignment using regression models based on time-domain features computed from vibration and sound sensors.

Efforts have also been made to diagnose gears faults using low-cost acoustics-based solutions [108]. A test rig was developed which could generate acoustic data from a gearbox in healthy and faulty states. Various time-domain and frequency-domain features were evaluated under different rotational speeds to detect a faulty condition. The proposed solution was based on a low-cost microcontroller and was shown to perform equally well when compared to COTS-based data acquisition systems.

Modulation Signal Bi-Spectrum is another technique applied on airborne sound for diagnosing failures in reciprocating compressors. A detailed study has been carried out on the planetary gearbox of wind turbines [109]. A fusion-based method is proposed which combines information sensors including electrical, acoustic, and vibration sensors. Features are computed from the energy of fault frequency computed from PSD estimation of signals. ROC curve is then used to compare results from various fusion parameters. Acoustics for wind turbine health monitoring has also been evaluated in Ref. [110]. It is stated that the installation of multiple microphones inside a wind turbine blade can be used to monitor cracks development. This study is conducted on a wind turbine blade that was undergoing fatigue testing. A total of 6 microphones are placed inside the blade and a subset of data is retrieved where the onset of cracks is noticed. Several signal processing techniques are applied for feature extraction. This includes time-domain parameters, cepstral coefficients, short-time energy, and zero crossings. Focus is given to Linear Predictor cepstral coefficients due to their popularity in audio signal processing. Dimensionality is further reduced using PCA and K-means clustering which is applied to the top 3 PCA components. Results are compared with features consisting of ZCR (Zero Crossing Rate), short-time energy, and first LPC coefficient only. The results show that the former set of features is robust in indicating deviation from a healthy state.

Very little information is available in the public domain literature that covers aspects of acoustics signal processing for gas turbine fault diagnostics. Nevertheless, an industrial gas turbine had been subjected to three different kinds of faults and acoustic data was collected for onward processing and fault diagnostics [111]. The sensors were installed around the compressor which had been subjected to rotor fouling, blade twisting, and mistuned stator vanes faults. Wavelet transforms were used to analyze the differences in acoustics signals during healthy and faulty conditions. The microphone signals displayed a shift in energy to higher frequencies in the case where stator vanes were restaggered. Finally, the difference between wavelet coefficients from the healthy and faulty engine was declared to be a robust feature for fault diagnostics due to the reduction in the number of features as compared to Fourier analysis.

Acoustics have also been of interest in the automobile sector where the focus has been towards understanding the sound generation from engines and determining possible ways of noise reduction [112]. The same phenomena have been utilized by researchers for evaluating engine noise as a source of information for fault diagnostics. Combustion noise was found to be the dominant source of noise for a diesel engine and is proportional to cylinder pressure [94]. Furthermore, time-frequency domain analysis can provide useful information about the engine firing order and crank angles. Automobile engine signals belong to the category of cyclo-stationary processes due to their reciprocating nature. This type of signal comprises repetitive cycles and is best observed with the help of time-frequency domain analysis. This information was utilized in Ref. [113] in which faults were induced in the engines and sound signals were used to differentiate between healthy and faulty conditions using Continuous Wavelet Transform (CWT). During the experimentation, it was noted that the lower frequencies are greatly affected by environmental factors, whereas the higher frequencies are more stable and provide robust features. Considerable improvements were made in Ref. [114] in which various wavelet domain features were studied and the appropriate ones were selected using the correlation-based feature selection method. This method aims to provide a subset of features that are uncorrelated with each other but are correlated with the fault under study. This is achieved by searching for a subset of features using a best-first algorithm, which provides the maximum gain or mutual information. The overall approach was declared to be robust in detecting faulty combustion conditions of an automobile engine, even in the presence of environmental noise. In another approach [115], envelope spectrum was obtained from sound signals and a correlation coefficient was used to segregate between the healthy and damaged engine.

The literature survey conducted on acoustics-based diagnostics reveals that the research community has approached this problem using data-driven techniques and the underlying noise generating mechanisms have not been the object of their study. Experimental data is usually collected from healthy and faulty states and models are trained to classify the faults based on measured data. Furthermore, the tests are conducted in a very controlled environment where other sources of noise are generally not present. In certain situations, certain conditions are set which may render the developed strategy impractical. Conducting the tests in an anechoic or semi-anechoic chamber and experimenting on the only subset of the whole machine are examples of such unrealistic scenarios. It has also been learned that for achieving repeatability in the data, the microphone should be placed at a distance that is greater than the engine length [94]. This condition may get satisfied for land-based systems but may not be possible for airborne platforms in which the systems are compactly placed and there is very little room available for mounting additional sensors.

3.5. Other forms of diagnostics

Certain elements, other than performance parameters and vibration, can also be used to estimate the current health of gas turbines. Using spectrometric oil analysis to predict the RUL of aircraft engines is one such method [116]. Total metal concentration computed from oil analysis has been proposed for engine failure prognosis. Wear debris analysis of lubrication can also determine the amount of wear occurring due to sliding, rolling, rubbing, abrasion, etc [51]. In Ref. [117], the importance of electrically charged particles for engine health monitoring is described. It is shown that these particles can appear in exhaust flow due to turbulent flow the increase in these particles is related to failures like abnormal loss of blade coating material due to on-going damage. As per the comprehensive survey carried out by Ref. [118], several diagnostics techniques are available for identifying failures in turbine blades and combustion chambers which constitute hot components of a gas turbine. The foremost method is of using various types of tip-timing sensors (magnetic, optical, capacitive, etc) provides information about cracks, creep and wear of turbine blades. Strengths and limitations of using temperature, pressure, vibration, mm-wave ultrasonic, and Acoustics Emissions for blades health monitoring have also been critically evaluated for various types of failure modes.

Another approach for engine health monitoring is to combine the results from various sensors to increase diagnostics coverage and making the results more robust and reliable. A practical example is discussed in Ref. [119], in which an information fusion system for the P&W F117 turbofan engine is developed using gas path measurement, accelerometer data, and oil debris analysis. The Fuzzy Logic method is another way of combining data from various sources for turbofan engine diagnostics [120]. Details of another fusion method are presented in Ref. [46] in which performance and vibration data are fused for gas turbine fault identification. The proposed GPA is based on a non-linear method that provides deviation from healthy conditions and the irrational results are leveraged by vibration measurements by fusing it using PDF integration followed by fusion using certainty factors. The vibration data used for validation was in terms of RMS values from 4 locations on the engine. Machine Learning techniques may also be applied for sensor data fusion. Neural Network techniques have been applied to performance and mechanical data acquired from engines in transient and steady-state fault diagnostics. A detailed survey has been carried out on sensor fusion techniques for condition monitoring of gas turbines using vibration data and GPA [121] which covers a comparison between different signal processing and probabilistic techniques. Another practical example of using multiple heterogeneous sensors for gas turbine fault diagnostics is presented in Ref. [122] in which data from 35 sensors were used to formulate a diagnostics model. The model was developed using hierarchical clustering and self-organizing map neural networks and was shown to perform well under steady and transient states.

Novelty detection framework development is yet another way of predicting failure in a system using information from multiple sources. The approach is to develop a high-dimensional system model using engine data in healthy states. This model is then used to monitor any significant departures from the normal state which may be an indication of failure onset [123]. This technique may not be directly applicable towards fault classification, but it can be used for detecting excessive vibrations or any other abnormal conditions which can damage the engine. This is because in real-life applications complete dataset is not available for various states of engine operation. Therefore, it is convenient to resort to novelty detection instead of the classification approach. Models for novelty detection are generally data-driven, and one such method based on advanced Machine Learning is discussed in Ref. [124].

3.6. Design considerations in aircraft systems with novel architectures

Airborne systems' reliability has been a cause of concern for all the stakeholders. Whether it is the design phase, or any other part of a product's life cycle, incorporating diagnostics capability into the system is desired. Even with technologically advanced systems, failure is inevitable. A failure can originate at a component level, triggered by foreign object damage, human error, or any other unforeseen circumstances. However, by carefully assessing the hazards and putting systems in place for risk mitigation, the frequency of occurrence of failures can be drastically reduced. To detect and respond to such failure conditions, a well-designed fault diagnostic system is integrated into an aircraft. The diagnostic capability is crucial for quickly responding to a failure condition by executing requisite measures. As the aircraft are being equipped with a greater number of systems, the overall complexity is increasing and therefore the importance of detecting and diagnosing failures cannot be ruled out.

With the significant projected increase in air travel [125], futuristic aircraft would be required to be greener, fuel-efficient, high performance, and less noisy. In this section, various novel aircraft architectures will be discussed from the aspect of their diagnostic capability. Starting with distributed propulsion technology, a detailed review is presented by Ref. [126] on the evolution and challenges associated with such technologies. Another review by Ref. [127] acts as a supplementary article and brings in military aircraft and UAVs within the scope as well. The distributed propulsion technology is said to cover a diverse range of aircraft, ranging from VTOL-aircraft to supersonic aircraft. The authors revisited the historical advances which have been made towards the design or development of aircraft with distributed propulsion systems, that can operate in subsonic or supersonic flight regimes. By distributing the thrust generation, the key benefits include noise reduction and better performance. Increased reliability can also be achieved by adopting a fail-safe mechanism in case of a diagnosed failure. As per the author, since superconducts is becoming a reality now, using distributed fans instead of small gas turbines is a better option. A novel concept is proposed by Ref. [128], in which a series of multiple electrical fans are integrated within an aircraft wing to generate the necessary thrust. The design involved multiple ducts and nozzles within a split-wing and posed several challenges. As per [129], the research community benefited from the design which incorporated multiple ducted fans for propulsion and employed a similar concept when designing VTOL/STOL aircraft. The use of electric propulsion for such types of aircraft has also been explored. In this regard, NASA's Puffin electric tailsitter VTOL concept is identified to be a highly reliable and efficient design [130]. In the case of the UAVs, the propulsion system is the most critical and is found to be the most common cause of a UAV failure [131]. Therefore, various electric solutions have been explored and tested for reliability using Hardware-in-the-loop simulations [132].

As the trend in the aviation industry is moving towards a more electric architecture, it is envisaged that the hydraulic/mechanical linkages will be replaced by electronic components. This will result in the reduction of the number of moving parts and therefore maintenance costs will decrease [133,134]. Using a high level of DC voltages on board the aircraft has also been proposed in Ref. [135], which will reduce the transmission losses through the aircraft electrical system. However, such a design would require the development of an advanced system for detecting faults in the aircraft power generation system. The turbofan engines are also being studied to incorporate electrical generators within the engine, as opposed to the generators are being driven by the low-pressure turbine through a mechanical drive [133,134]. The standard diagnostic practices may not be applicable to such designs if they are made practical.

There are several technical challenges involved with the above-mentioned innovative aircraft architectures. For example, in the case of a distributed propulsion system, the common problems which have been identified are engine cooling and loss of airflow and thrust by the rear engines. Fabrication and manufacturing of unconventional aircraft structures along with the integration of a distributed propulsion system in the airframe are also considered high-risk tasks that should be overcome before proceeding with further development.

4. Application of acoustics in airborne gas turbine engines

Acoustic power or sound energy from an aircraft originates from its engines, auxiliary power units, high-lift systems, landing gear, and propeller. Such unwanted Acoustic noise has been classified to be "annoying" for the people living around the airports [136]. It can even have adverse effects on the health of airline employees leading to partial or complete hearing loss [137]. Owing to such serious implications, aircraft regulating authorities have put restrictions on airline operators and airports to limit noise generation. This can be achieved by reducing noise at the source, modifying flight procedures, or by restricting flight operations. Ideally, technological improvements to existing and future aircraft and engines can help in reducing noise radiation from the source without hampering the operations. Thus, the research community has been considerably involved in developing methods to ascertain noise-producing mechanisms and their abatement. Since the object of this review is to appraise the reader about various aspects of airborne engines' noise, so the following sub-sections will be limited to turbofan, turboshaft, turbojet engines, and auxiliary power units.

4.1. Gas turbine noise terminology

To proceed further and learn more about airborne gas turbine noise and its characteristics, it is necessary to understand the terminology commonly used by the industry as well as the research community. These terminologies are associated with gas turbine noise and have been frequently used in the literature.

4.1.1. Engine core noise

The term 'engine core noise' has been coined for the phenomena which contribute towards engine noise upstream of the nozzle exit (Fig. 5) [138]. The core-noise mechanisms are engine specific and become dominant when the jet velocities are considerably low (for example a turbofan engine on idle when the aircraft is at approach). As per [139], core noise consists of combustion noise, low-frequency noise generated in the turbine as a result of interaction with upstream turbulence from the combustor, noise generated in the flow passage discontinuities (turbine exit struts), and turbulence level and swirl in mean flow upstream of the nozzle exit. In certain cases, jet-noise/jet-mixing noise is excluded from core-noise category [140].

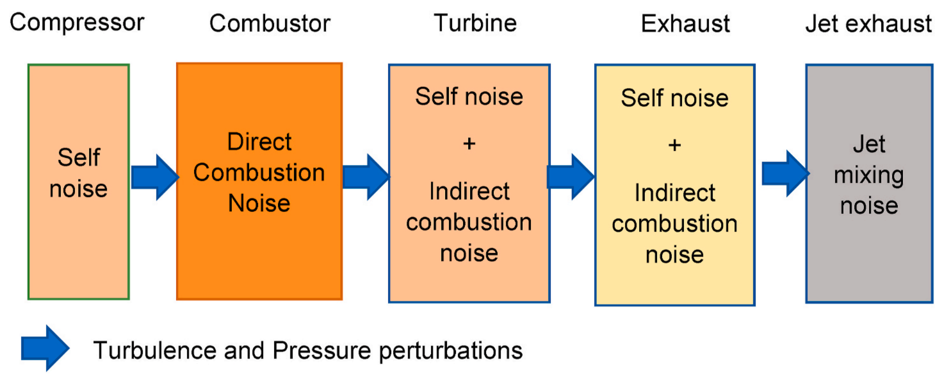

Fig. 5. Engine Core Noise [138].

4.1.2. Direct combustion noise

It is related to the acoustic waves which are generated due to the turbulent combustion process and are propagated through the turbines.

4.1.3. Indirect combustion noise

This is the name given to acoustic waves which are induced by convection of combustion-generated heterogeneities like temperature fluctuations/turbulence through mean velocity gradients appearing through turbine blades or nozzles.

4.1.4. Tonal noise

It is produced by a regular rotation of turbomachinery blades (compressors and turbines). This tonal noise is mainly present at high frequency and radiates through the air intake in case of compressors and the exhaust in case of turbine stages. It is possible to characterize the sound pressure frequencies with the Blade Passing Frequency (BPF) which corresponds to the revolution rate per second times the number of compressor or turbine blades [141]. The compressor noise may be masked by fan noise in the case of turbofan engines [142].

4.1.5. Broadband noise

This is the noise that has greater spectral content as compared to tonal noise. This is caused by pressure fluctuations associated with the turbulence in the flow field. Fans are a major contributor to this kind of noise because of the vortex shedding occurring at the blade trailing edges [143]. Jet noise is the noise generated from the high-velocity engine jet mixing with slower ambient air [144].

4.1.6. Casing-radiated noise

The noise generated by internal components of a gas turbine may radiate through the casing of the gas turbine assembly. This noise leaves the engine and will be picked up in the near vicinity of the engine. This form of noise is termed the casing-radiated noise. This noise experiences sound reduction when it passes through the engine panels and is therefore an attenuated version of the actual noise present inside the engine [145]. In general, this type of noise depends on the internal noise, geometry, and stiffness of the casing [146].

4.1.7. Sound power

Any item of equipment that generates noise radiates acoustic energy. The total amount of acoustic energy it radiates is sound power. This is, generally, independent of the environment [145]. Sound Pressure Level is the sound pressure acting on the sensor or human ear. The sound pressure is very dependent on the environment and the distance from the noise source to the listener. SPL is the RMS value of sound pressure signals.

4.1.8. Sound intensity

It is the amount of sound energy radiated per second through a unit area. If a hypothetical surface, or envelope, is fitted around the noise source, then the sound intensity is the number of acoustic watts of energy passing through 1 m^2 of this envelope. The sound intensity, I, normal to the spherical envelope of radius, r, centered on a sound source of acoustic power, W, is given by:

$$I = W / 4 \pi r^2$$

4.1.9. Overall Sound Pressure Level (OASPL)

It is the Sound power level obtained by integrating power in all the frequency bands. Let S(f) be the power spectral density of sound, then

$$\mathrm{OASPL} = 10 \log_{10} (E) \text{ [units: dB], where } E = \int S(f)\, df$$

4.1.10. Metric for engine noise

Most of the acoustic parameters are expressed in terms of decibels because of the huge range of levels that are possible. During conversion to decibels, a reference pressure of 20×10^{-6} Pa is usually selected.

4.2. Significance of engine core noise

Generally, gas turbine noise is studied to provide insight into its physics, develop empirical prediction models, separate noise sources for

Table 3
Categories of features for diagnosing gearbox faults [54].

Category	Technique	Metric
RAW signal (RAW)	Features from the raw signal	RMS, Kurtosis, Delta RMS, Crest Factor, Enveloping and Demodulation.
TSA	Synchronous averaging of raw data (results affected by interpolation factor, number of revolutions concatenated during alignment, and number of averages)	FM0, Kurtosis
Residual signal (RES)	Removal of Primary meshing and shaft components along with their harmonics	NA4 andNA4*
Difference signal (DIF)	Removal of regular meshing components from the time-synchronous averaged signal	FM4, M6A, and M8A
Band-pass mesh signal (BPM)	TSA signal is band-pass filtered around the primary gear mesh frequency, including as many sidebands as possible	NB4

Table 4
Summary of Experimentation done on Gas Turbine Noise.

Year	Type of Engine	Acoustic Suppression	Acoustic Sensors	Other sensors	Experiment Location	Observed parameters	Operating Conditions	Target Objective	Prediction method compared with
1977 [149]	P&W JT8D-9 & Rolls Royce Spey 512 Turbofan engines + Olympus 593 Turbojet	Standard	Far-Field microphone array (placed on the ground)	Nil	Not mentioned	1/3 Octave band up to 1 kHz	Not mentioned	Study combustion and jet noise	Temperature fluctuations
1988 [163]	Turboshaft engine - 90k RPM, 8 kW, radial compressor and turbine	No	Nil	2 vibration sensors installed on combustor and compressor	Not mentioned	Frequency Spectrum up to 21 kHz	Idle, 50%, 75%, Full Load	Effect of fuel type on induced vibrations	Nil
2008 [150]	TECH977 demonstration engine	Standard	32 Far Field Microphones (100 ft radius)	In-duct sensors	Open Environment	Frequency Spectrum up to 10 kHz + Directivity	48%, 54%, 60%, 71%, 87%, and 91%	Study noise and noise reduction methods	ANOPP
2008 [151]	TECH977 demonstration engine	Standard	Far Field microphones array + 16 Internal sensors in Combustion chamber	Nil	Open Environment	Frequency spectrum up to 10 kHz	24%, 48%, 54%, 60%	Study turbofan noise engine by taking measurements with and without the fan	Nil
2008 [153]	ANTLE demonstrator engine (Rolls-Royce Trent 500)	Standard	6 Microphones (7.25 m from exhaust) + Internal sensors	Nil	Test Cell with acoustic treatment	Frequency spectrum up to 1 kHz	35%, 40.5%, 43.6%, 46.1%	Study combustion noise	SAE 876D
2009 [154]	TECH977 demonstration engine	Standard	Far Field microphones array + 16 Internal sensors in Combustion chamber	Nil	Not mentioned	Frequency spectrum up to 1 kHz	48%, 54%, 60%	Study Direct and Indirect combustion noise based on time delay analysis	Nil
2009 [155]	FJ44 Turbofan	Standard	3 Array of microphones (2 side, 1 front - Total 48 microphones - 16 ft distance)	Nil	Anechoic chamber	Order Spectrum up to 120 of N1	69%, 85%, 100%	Effect of acoustic line at inlet, dominant noise production mechanisms	Nil
2011 [140]	GE Turbofan engines	Standard	Not mentioned	Nil	Not mentioned	Frequency Spectrum up to 10 kHz + Directivity	Low Power, High Power	Study noise from components	ANOPP
2014 [153]	Ardiden 1H-1 Turboshaft engine	No	34 Internal, 18 in Far-field at 19.2 m	Thermocouples in combustor and HP Turbine	Open Environment	Correlation + Frequency Spectrum up to 4Khz + Directivity	Low and high power	Identification of noise sources and contribution towards total noise emission	Nil
2018 [142]	DGEN 380 turbofan engine	Standard	24 Microphone array (12 m from exhaust)	Internal pressure sensor in the core-nozzle exit	Anechoic chamber	Frequency spectrum up to 1.6 kHz	60%, 70%, 80%, 90%	Study combustion noise	Nil
2019 [164]	SR-80 Turbine Engine	No	2 microphones (1 m from combustion chamber at 90° and 45° from exhaust)	Thermodynamic sensors, Triaxial Vibration sensor, MultiGas FTIR Spectrometer	Open Environment	Frequency spectrum up to 16 kHz	Fixed RPM	Comparison in noise, vibration and emission for 2 different types of fuel	Nil
2019 [159]	DGEN 380 turbofan engine	Standard	24 Microphone array (12 ft arc)	Internal pressure sensor in the core-nozzle exit	Anechoic chamber	1/3 Octave band up to 2 kHz + Directivity	50%, 60%, 70%, 80%	Study combustion noise	ANOPP

validating results, and eventually developing noise suppression methods. In literature, more emphasis is given to combustor noise because it dominates the lower frequencies and is thus difficult to curtail when dealing with noise abatement. In Ref. [138], the significance of core noise for turbofans in low-power settings and APUs is also explained. As per [147], jet noise was initially very high and its contribution towards overall noise was significant. As jet noise depends on the 8th power of jet speed – so increase by a factor of 2 will increase noise by 50 dB. Jet speed reduction was at the time not only a noise concern but also a performance requirement, since the propulsive efficiency increased significantly when the jet speed was reduced, increasing aircraft range and reducing cost. The turbofan engine used nowadays achieved these goals by reducing jet speed and maintaining the total thrust by increasing the mass-flow using a by-pass design. Now the major source of noise is from fan and turbomachinery noise at higher power settings. Moreover, when the aircraft is in flight, the relative difference between jet velocity and the ambient velocity decreases and so does the jet mixing noise thus making direct and indirect combustion noise to be more prominent [148].

4.3. Gas turbine noise measurement and characteristics

Extensive measurements have been taken around engines of various sizes and configurations to construe noise-producing mechanisms and subsequently quantifying the effect of the noise suppressing arrangements. Owing to the massive size of turbofan engines, sound measurements are acquired using a large anechoic chamber or a ground with no obstructions for producing meaningful results. Also, the measurements are generally made with multiple microphones placed in the far-field of the inlet or exhaust. Table 4 presents a summary of different types of experiments that have been performed on airborne gas turbine engines. Each entry in the table gives information about the engines under study, the nature of the experiment, and the objective of that activity. The salient features of each activity are explained in the subsequent paragraphs.

In [149], the theory of the relationship between acoustic power and temperature fluctuations from combustor was validated using noise measurements from three aero-engines. The overall contribution from this source exceeded jet mixing noise at low jet speeds. By assuming temperature fluctuations to be 2% of the mean static temperature into the turbine, it was shown that the exhaust noise at low power settings was related to the average temperature fluctuations for all three engines.

In a detailed report by NASA-funded research on integrated technologies for aircraft noise reduction, a turbofan engine was used to establish baseline noise measurements [150]. Extensive measurements were taken at NASA Glenn Research Centre using the TECH977 turbofan engine with microphone arrays and acoustic barriers to separate inlet and exhaust noise. Case radiated noise was also studied and found to be in a lower frequency range caused by flow in c-ducts. The analysis revealed that the combustion noise was present at 250 Hz and multiple resonating frequencies are also generated from the combustor. With respect to the jet noise, it was observed to be reduced with a decrease in power and appeared in the low frequencies. Effects of various acoustic treatments on engine noise levels and directivity were also studied. The noise sources identified by this program are presented in Fig. 6. The combustion and jet noise are overlapping in the lower frequency range while fan noise is in the intermediate range and turbine noise is contributing to the end of the spectrum.

A separate study was conducted on a turbofan engine with and without the fan, with an aim to develop a better understanding of the combustion and turbine noise [151]. This was a sub-task of NASA's Engine Validation of Noise and Emissions Reduction Technologies (EVNERT) program. The engine had to be modified so that it could be operated without the fan. This removed the tonal and broadband frequency content which is generated from a fan. Moreover, internal pressure sensors were installed so that the internal dynamics of the combustor can be better understood. It was discovered that there were broadband peaks inside the combustor, which can be the result of resonance. However, these peaks were not present in the far-field data. In addition to this, very little change was observed in combustor noise spectra amplitude at different engine operating speeds but was accompanied by a slight change in frequencies. The combustion noise was found to be the dominant source in the 250–1000 Hz range, whereas turbine noise was in between 5 and 10 kHz. Complete engine (with fan) acoustic response was also compared with prediction models and the major discrepancy was found in the 1250–4000 Hz range where the fan duct acoustic treatment was present. In the same study, case radiated noise was analyzed using phased array configuration of multiple microphones. The transition portion of the c-duct was found to be the prominent source of casing-radiated noise which was present between 100 and 700 Hz. This noise was considerably reduced at lower power settings.

In [152], various signal processing techniques were applied to determine the contribution of noise sources on the overall acoustic behavior of a turbofan engine in the far-field. The three-microphone method produced desirable results where the sources did not overlap in the frequency domain and only a single source was dominant.

A study on combustion noise from a large turbofan engine was undertaken as part of the EU Silencer(R) (Significantly Lower Exposure to Aircraft Noise) project [153]. The spectral coherence technique was used to study the relationship between data from data captured from internal sensors and far-field microphones installed around Rolls-Royce Trent 500 aero-engine. Experimental results support the presence of low-frequency direct combustion noise (below 100 Hz) which was not affected by the change in engine shaft speed. Furthermore, indirect combustion noise is found to be present in the 100–1000 Hz range. Eventually, two spectrums were defined to represent direct and indirect combustion noise, with peaks at 160 Hz and 200 Hz respectively. The results were compared with the SAE prediction model which predicted combustor peak at 400 Hz, but the noise levels and the directivities were similar. systems.

Rigorous analysis of TECH977 turbofan acoustic data was done in order to characterize the core-noise [154]. Time delay analysis was performed to maximize coherence between combustion chamber signal and far-field acoustic data. For this specific engine, direct noise was present in the 200–400 Hz frequency range and indirect noise due to interaction of entropy fluctuations with downstream components lead to noise in the 0–200 Hz range.

Microphone arrays have also been employed for turbofan engine's noise source identification [155]. A 48-microphone array system was installed at 60–193 inches from the FJ144 engine, which aided in specifying the region of interest and subsequently spatial filtering of inlet and exhaust noise. All the necessary analysis was done with the engine being operated inside an anechoic chamber. The principal observation that was made referred to the presence of multiple tones from the inlet in the exhaust noise spectrum, provided they were greater than the exhaust noise levels. Another peculiar behavior was the location of jet mixing noise, which moved closer to the nozzle exit with an increase in frequency. Moreover, as the jet flow speed was increased, the peak turbulent mixing noise moved further downstream of the nozzle exit. Towards the engine inlet, the noise was found to be emancipated from the edges of fan blades.

In another publication by NASA [140], the engine noise prediction model is iteratively developed, and its validation is made using multiple turbofan engines. Primarily, the attention is towards the broadband combustor noise which is corrupted by the jet noise in the same frequency range. The notion of single peak combustor noise is debunked in this study, due to the presence of four core-related peaks. However, since the fourth peak is masked by the turbomachinery noise towards higher frequencies, a three-peaks combustor model is proposed. The proposed method is said to be effective for the engines under study, however, improvements can be made by comparing the results with other engines using the same methodology.

In [156], a study was conducted to understand the relationship between combustor and turbine noise with far-field noise for a turboshaft engine. This activity was part of the EU-funded TEENI (Turboshaft Engine Exhaust Noise Identification) project. Various techniques like coherence, coherence output power, three and five microphone signal enhancement techniques were employed for better accuracy. The analysis showed that the sound power spectrum can be divided into 5 bands where noise from various engine zones is making contributions. The first band is of combustion zone ranging from 100 to 260 Hz, the second is designated for indirect combustion noise (260–600 Hz), third for turbomachinery noise from a high-pressure turbine, and so on. This study does not deal with jet noise due to the assumption that the jet velocity is negligible for turboshaft engines.

In another study [157], the three-signal coherence method was applied to study the origin of broadband noise for turboshaft engine which had been instrumented with internal sensors and far-field microphones. With the aid of numerical simulation, it was shown that the three-signal method can extract narrowband sources corrupted with background noise. The method also outperformed the conventional signal processing techniques when applied to measured data. It was eventually concluded that the broadband component is developed due to multiple turbine stages and is a result of indirect combustion noise. Furthermore, combustion noise was identified at low frequencies (200 Hz). Another type of experimentation on turboshaft engine was undertaken by Ref. [158] in which three-dimensional evaluation of noise was done. It was found that the sound directivity was focused towards the sky and conventional methods of measuring sound directivity were not enough to pick up such response.

NASA's Glenn Research Centre houses Aero-Acoustic Propulsion Laboratory which has been used for noise measurement of several engines. As per [142], this facility was used to acquire a baseline dataset for a DGEN 380 turbofan engine. The tests were conducted inside an anechoic chamber with two internal and several far-field microphones. Using two-signal source separation, broadband combustion noise was found to be present in the 100–500 Hz range. The frequency range of the combustor-noise component was also observed to be increasing with the rise in power level.

Using the same engine, noise measurements in 1/3 Octave band were compared with ANOPP (Aircraft NOise Prediction Program) noise prediction model [159]. It was found the ANOPP model was not able to accurately predict the combustion noise. There was a shift in directivity and a presence of a second spectral peak was observed which is not modeled by the ANOPP subroutine for combustor noise. Emphasis was towards the understanding of combustor noise. In a similar study conducted on the TECH977 turbofan engine [160], it was observed that the direct and indirect combustion noise share the same frequency spectrum, but their spectral shapes could be quite dissimilar.

Acoustics has also found its application in measuring gas turbine exhaust characteristics using sonic anemometry. In Ref. [161], the aim of the experiments was to map the temperature profile at the exhaust of a power generation gas turbine. Eight-channel transmitter-receiver pairs were placed around the exhaust and average temperatures were computed using flight-time, distance information, and gas properties. The received signals were corrupted by machine noise and had to be filtered out by disregarding highly noisy time-frequency bins and complementing the results with statistical models. However, the method led to several inaccuracies due to the presence of temperature and velocity gradients which affect sound propagation. For higher Mach numbers, the straight-line propagation model of sound is not valid and the flow velocity's effect on acoustic propagation has to be modeled [162]. This methodology produces many accurate results and utilized only two microphones.

Effect of fuel on gas turbine noise and vibrations have also been recorded in the literature. Effect of fuel type on combustion-induced vibrations was investigated for a turboshaft engine in Ref. [163]. It was noted that the vibration spectra were similar for compressor and combustion vibrations. Combustion was found to induce vibrations at higher frequencies (above 1 kHz) and vibration levels increased with an increase in RPM and load. Since the scope of this study was limited, the vibration spectra cannot be treated as a reference model for other gas turbines. Likewise, in Ref. [164], the effects of two different fuel types on noise, vibration, and emission were studied for a turbojet engine. Noise measurements were taken very close to the combustor (at 1 m) and the exhaust. The engine was also equipped with thermodynamic sensors, a spectrometer, and a triaxial accelerometer for recording vibrations. Change in fuel type resulted in a slight variation of low-frequency noise which may be because of a variation in combustion characteristics. A detailed analysis was not performed, and the data acquired at two different instances were inconsistent. Therefore, the results cannot be treated as baseline measurements for the turbojet engine.

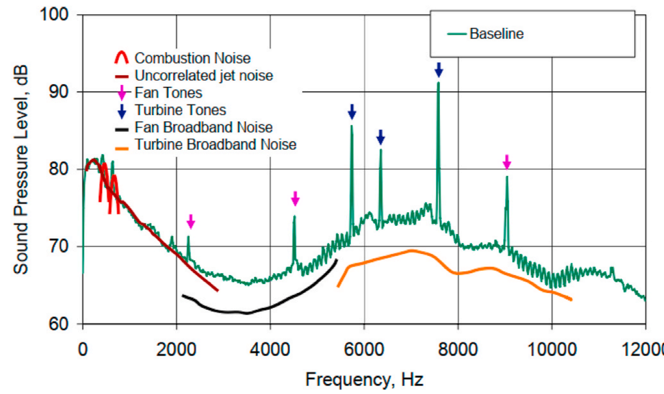

Fig. 6. Baseline engine far-field noise and identified noise sources [150].

Independent studies have also been carried out to characterize the acoustic behavior of combustion processes only. In Ref. [165], various sizes of burners were used and were subjected to varying flow velocities and equivalence ratios. The results indicated that the acoustic spectrum was broadband in nature with its peak slightly changing with burner's diameter (proportional to $D^{-0.8}$) and there is a $f^{-5/3}$ decay in 800–3000 Hz range. Another peculiar behavior was of equally spaced local maxima which occurred after the peak frequency. Total flame noise was found to be a function of fuel ratio and flow velocity. Moreover, Flame tip reduction led to a drop in low-frequency energy. The analytically driven relationship for direct noise indicates that acoustic power varies proportionally (4th power) of flame speed but this phenomenon does not incorporate combustion noise radiation in the high-frequency range (indirect-combustion noise) [166].

An altogether different nature of the study has been undertaken by Ref. [167] which investigates the possibility of reducing the total noise radiated by an aircraft by modifying its landing trajectory. The study relies on the aircraft noise data that is simulated using a combination of semi-empirical relationships and physics-based models which consider the aircraft geometry, engine state, and flight mechanics. The simulations are then carried out for different glide slopes and it is found that there is the scope of noise reduction on landing by increasing the glide slope angle. However, this would require an extension of the runway by 450 m and an assessment of this approach concerning flight safety. Moreover, the claim is also required to be substantiated by experimentally acquired measurements.

4.3.1. *Discussion on gas turbine noise experiments*

Several inferences can be made after conducting a literature survey in the field of gas turbine noise measurements. Firstly, relatively more information is available for turbofan engines, as compared to turboshaft and turbojet engines. This is clearly due to the huge demand for turbofan engines in the aviation industry because of their impressive performance

Table 5
Summary of Experimentation done on APU Noise.

Year	Number/Type of APU	Acoustic Suppression	Acoustic Sensors	Other sensors	Experiment Location	Observed parameters	Operating Conditions	Target Objective	Prediction method compared with
1968 [168]	GTCP-36-4	Yes	Not mentioned	Nil	Not mentioned	Frequency spectrum up to 10 kHz	No Load + Full Load	Study noise sources and develop attenuation methods	Nil
1978 [169]	GTCP - 85 series APU	No	6 Internal, 8 Near-Field and 8 Far-Field (25 ft radius)	Nil	APU inside Acoustically isolated chamber	Frequency Spectrum up to 1 kHz	No Load + Full Load (Full bleed and electrical power)	Correlation between internal and external sensors in order to characterize noise sources	Nil
2005 [178]	3 Different APUs (GTCP-36-150, RE220, 321-600)	No	24 microphones (12 on pole + 12 on ground) at 25 ft from APU exhaust	Nil	APU inside Acoustically isolated chamber	Frequency spectrum up to 12 kHz	low, mid, high power	Study spectral shape of combustion noise	Similarity spectra
2007 [170]	APU of 5 Aircraft	Yes	8 circularly placed microphones	Nil	Aircraft	Frequency Spectra up to 10 kHz + Directivity	No Load - ECS	Develop reference dataset for APU noise	Nil
2010 [137]	Multiple (10 Aircraft)	Yes	Multiple (around aircraft tail-sections + sensors worn by employees)	Nil	Aircraft	1/3 Octave band up to 20 kHz	All conditions	To study occupational noise due to APU operation	Nil
2010 [195]	Multiple Aircraft (767,747,A310)	Yes	1 Microphone (around 20 ft from APU Exhaust)	Nil	Aircraft	Average Sound Levels	Not mentioned	Assess effect of noise on employees	Nil
2011 [171]	1 APU (Specs not mentioned)	Yes	24 (25 ft from exhaust) + 31 (3 ft radius from inlet)	Nil	APU inside Acoustically isolated chamber	Frequency spectrum up to 8 kHz + Directivity	Electric Load only - ECS and Electric loads	Measure attenuation of inlet and exhaust treatments	Numerical Analysis
2012 [196]	APU Compressor only	Yes	Microphone array around inlet only	Unsteady pressure sensors	APU inside Acoustically isolated chamber	Frequency spectrum up to 3 x BPF	90%–100% RPM	Inlet noise prediction due to impeller shock wave	Numerical Analysis
2012 [179], 2013 [197]	RE-220 APU	No	10 internal sensors placed around combustor + 6 pressure sensors in the exhaust pipe	Nil	Room with no acoustic treatment	Frequency spectrum up to 6.5 kHz	Not mentioned	Identify the presence of indirect combustion noise	Numerical Analysis
2014 [172]	GTCP-36-300	Yes	25 Far Field sensors (25 ft radius)	Nil	APU inside Acoustically isolated chamber	1/3 Octave band up to 10 kHz + Directivity	ECS only and MES only	Effect of muffler design on noise attenuation	Nil
2017 [124]	GTCP-85-129	No	Nil	1 accelerometer (2 kHz) at engine support	Not mentioned	Frequency Spectrum up to 1 kHz	3 Modes	Effect of fuel type on vibrations	Nil
2017 [174]	APS3200	No	3 (0.6 m from exhaust) + 1 in the chamber	Thermodynamic sensors, Exhaust Gas analyzers	Room with no acoustic treatment	Frequency Spectrum up to 10 kHz	25 combinations of electric and pneumatic loads	Effect of loading conditions on exhaust noise	Nil
2018 [173]	GTCP-36-28	Yes	3 microphones around turbine exit + 15 inside exhaust	Temperature + Pressure sensors	Room with no acoustic treatment	Frequency spectrum up to 12 kHz	No Load, Bleed load only, Electric + Bleed load	Study Attenuation of different exhaust mufflers	Nil
2019 [198]	GTCP-85	No	2 Microphones (1 m from APU)	2 accelerometers (x, y direction)	Room with no acoustic treatment	Frequency spectrum up to 500 Hz	No Load + ECS + MES	Comparison in noise and vibration for different types of fuel	Nil

and efficiency. With the increase in commercial aerial activities, overall noise levels will tend to rise which have to be curtailed with the advent of state-of-the-art noise reduction technologies at an equivalent pace. Aircraft engine noise is complex to understand due to the inherent complexities of sound generation and propagation. Therefore, the overall scale of experimentation has been quite large because of the requirement of a large number of microphones, spacious anechoic chamber, engine modifications, and in some cases acoustic barriers between inlet and outlet. The engines have been mostly modified to incorporate internal sensors in the upstream of the exhaust nozzle till the combustor. The sensors must be ruggedized to withstand the heat at various engine stages. Due to the above-mentioned reasons, engine noise has not been studied extensively while it is installed on the aircraft. Moreover, the measurements are mostly made in the far-field. Even the aim of the installation of internal acoustic sensors has been to correlate their information with the far-field data. Lastly, since all engines had axial compressors, very less information is available for the acoustic response of centrifugal compressors. Moreover, no efforts are seen to be made in using the information gathered from acoustics for health monitoring purposes. It can be observed that this field is considerably complex and requires an in-depth understanding of noise-generating mechanisms, engine dynamics, sound propagation techniques, and sensor limitations. The overall resources needed for carrying out detailed analysis should not be underestimated also. These could be the reasons because of which, acoustics have not gained much attention for engine fault diagnostics or health monitoring.

4.4. APU noise measurement and characteristics

Various forms of experimentation performed on APU noise are presented in Table 5 and similar to the gas turbine experiments, it is apparent that the focus has been towards the understanding of noise-generating sources and possible ways of their reduction. However, unlike the turbofan engines, APU noise has not been studied in greater detail and their levels have not been compared to any of the sound prediction models. In the following paragraphs, details of the experimentation or analysis performed on APU noise are presented.

A study on APU noise has been carried out in Ref. [168] to broadly the noise in order to develop attenuation methodologies. Major sources of noise were found to be from turbine exhaust, body radiation, cooling fan, and compressor inlet. Acoustic treatment of inlet was suggested so that fan and compressor noise is suppressed. On the other hand, the exhaust noise can be attenuated by a silencer. The author also suggested the installation of vibration isolators and a titanium enclosure for treating high-frequency surface radiated noise.

Core noise was characterized for a specific APU by performing correlation analysis between internal and external microphones for a range of 0–1000 Hz [169]. The APU with 06 internally mounted acoustic sensors was placed inside a soundproof box while an array of far-field sensors was installed in a circular manner. It was inferred that direct combustion noise dominated the far-field spectrum till 400 Hz. Two additional noise sources were also located which constitute the exhaust noise. Noise generation occurs between combustor exit and turbine which is due to the interaction of noise from combustor with the turbine. Another indirect source of noise is due to the mixing of engine exhaust with cooling air in the secondary duct. The results gave insight into the noise generation mechanisms but variation in noise features with loading conditions were not experimented with and analyzed.

In [137], average noise from APU of different aircraft was acquired in order to substantiate concerns of airline employees regarding exposure to noise while servicing the aircraft. Microphones were placed around the aircraft and attached to personnel working on the aircraft for measuring occupational exposure to noise. SPL (93–124 dB) and 1/3 Octave levels were recorded for various aircraft and procedures were recommended for reducing harmful effects on people. This study did not involve in-depth study of APU noise directivity and variation of noise with operating conditions.

An elaborate study has also been done in Ref. [170], where APU noise data was gathered from 5 aircraft with and without ECS operation in order to characterize noise from ground operations. With the help of

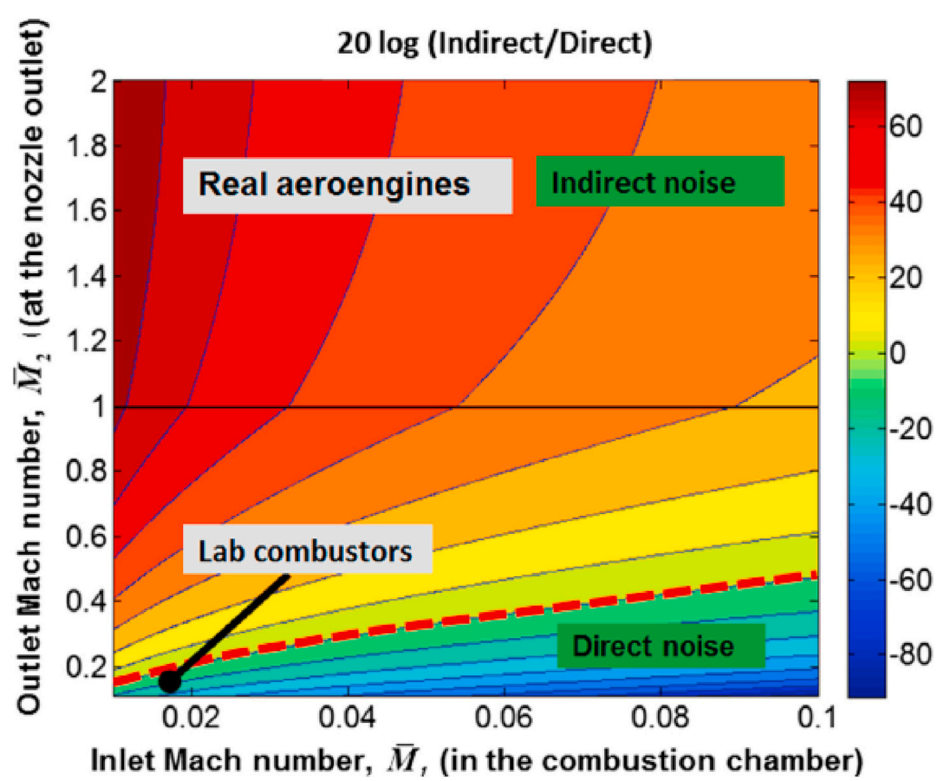

Fig. 7. Ratio of indirect to direct combustion noise (as a function of inlet and outlet Mach numbers at the flame zone and nozzle outlet respectively) [185].

circularly placed microphones, spectra and directivities were obtained for each aircraft at 1 m from the fuselage centre. Broadband noise till 10 kHz was observed for all aircraft in all directions when the air conditions were not operational. The directivity pattern was symmetric and exhibited minimum sound levels in the forward hemisphere while maximum levels were measured at 150° and 210°. Only A340 displayed slightly different results and had a non-symmetric pattern with a maximum level at 150° which is because of the off-centered placement of the exhaust outlet. It was also concluded that the APU operation with ECS did not produce a uniform change in noise features and no correlation was found between bleed air pressure and the measured noise.

Numerical analysis to predict the behavior of acoustically treated inlets and exhaust ducts of APU was performed in Ref. [171]. Experimental evaluation of the same was done by placing the APU in a soundproof room and it was found that the sound attenuation levels and directivities were in line with the predicted results. An experimental investigation was done in Ref. [172] to study the effect of different mufflers on noise reduction for a specific APU. Tests were conducted in an outdoor environment with far-field sensors placed in a semi-circle around the muffler exhaust while the APU was inside a wooden box. It was observed that Main Engine Start noise was more than for the ECS test which can be because of high flow rate and off-design operation. Moreover, noise attenuation for all the configurations was negligible for frequencies below 200 Hz which maybe because of the resonances induced by mufflers' geometry. Spatial directivities were also studied and found to be maximum at ±60° for higher frequencies and this deflection of sound occurs because of the shear layer between high-velocity jet with the surrounding airflow [173]. also claims to have designed mufflers for APU which perform well over a large range of frequencies. The cavities-based muffler design with bias flow has been proposed for better noise absorption.

An indoor activity with APU noise was performed in Ref. [174] where the APU was subjected to various loading conditions. The study was conducted in an enclosed chamber and noise measurements were taken very close to the exhaust. It was found that the overall noise level was mainly dominated by low-frequency broadband noise in the range of 20–300 Hz under all operating conditions. Moreover, maximum noise was observed at no-load condition because of the additional flow through the exhaust from the load compressor to avoid surge. The effect of fuel on noise and vibration of an APU with can-combustor was evaluated in Ref. [175]. Tests were conducted in a test cell and some variated amplitudes of vibration signals were noted for different configurations of fuel. This study lacks an in-depth analysis of spectral content and directivity of APU noise.

A narrowband combustion noise model has been proposed in Ref. [176], which was validated using APU exhaust noise data. The model captures the modulating behavior of the base spectrum by using a transfer function that describes the frequency response of the path from the combustor to exhaust. An approximation of similarity spectrum is used as the base, while the modulation function caters for the variations occurring due to engine geometry and EGT. The relationship was further improved by introducing the frequency-dependent damping function into SAE ARP876 [177] directivity function. Broadband peaks in the combustion chamber of a turbofan engine have also been witnessed in Ref. [151]. Experiments were carried out on a turbofan engine (with and without its fan) and the spectral shape of combustion noise was in line with the narrowband model prediction proposed by Ref. [176]. However, this behavior was only observed at an angle of 120° from the inlet. This model is applicable to turboshaft, turboprop, turbofan, and APUs [136] for far-field measurements.

Analysis of sound levels from 3 different APUs was done in Ref. [178] and it was found that they exhibit a unique spectral shape that does not depend on engine design, power setting, and directivity. This shape was coincidentally like the similarity spectrum of high-speed jet noise. The peak frequency remained in the range of 250–350 Hz for all conditions while the peak sound level varied proportionally to the square of fuel consumption rate. However, this required a scaling factor to be computed for each APU and hence the same relationship may not be extended to another system. Additionally, the presence of a secondary source of noise is debunked by the author.

The presence of indirect combustion noise in APU was investigated by relating experimental results with the theoretical model [179]. Indirect noise is said to be generated when entropy waves interact with a constriction. It was eventually established that the experimental results did conform to the model's prediction of indirect noise. However, it was suggested that further research should be undertaken to further substantiate the findings. Therefore, the claim of [178] was reevaluated using data from the same APUs [178,179]. By subtracting the similarity spectra of direct combustion noise from far-field data, noise peaks were reported at the frequencies which were predicted by model theory. This led the authors to conclude that APUs do generate indirect combustion noise. The study was further expanded to a broader set of acoustic data including measurements from turbofan engines [180,181] where the similarity spectra were again validated for combustion noise. It is also suggested that this method can be used to separate combustion noise from all other noise sources if the jet noise is low. Detailed numerical analysis was also performed to validate the presence of indirect combustion noise [182]. Simulations carried out by Ref. [183] for helicopter noise showed that the main constituent of turbine-exit noise is indirect combustion noise [147].

Engine core noise generating mechanisms were reviewed in Ref. [138] which also included a study on jet exhaust noise. It was argued that the assumption of direct and indirect combustion noise propagating directly to far-field neglects secondary noise generating mechanisms which are induced when the core noise exits the jet nozzle. Another relevant study is by Ref. [141], where it is argued that acoustic power due to jet noise follows the 6th power law and since the Mach number for turboshaft engines does not exceed 0.15, the contribution is negligible. According to Ref. [136], APU noise is not generally modeled together with aircraft noise because APU data is not sufficiently available and the noise radiating from APU undergoes interferences during propagation. However, SIMUL (German noise simulation program) implements combustor and jet models for predicting APU noise, and the combustion noise in APU peaks around 250–500 Hz. The writer in Ref. [143] posits that the APU noise is not generally modeled in the aircraft noise prediction software because of the scarcity of APU data. A standard by SAE (ARP1307) recommends procedures for conducting noise surveys around the aircraft However, it comes with a disclaimer that it does not provide ways of predicting APU noise from basic engine characteristics [184].

Similar to noise measurements, vibration data have also been analyzed for APUs [124]. The purpose of this study was to observe variation in vibration data when operated with various fuel types. The data were acquired at a sampling rate of 2 kHz and the accelerometer was placed at the base of the gas turbine. When conventional fuel was used, the broadband vibration spectra were observed with no tonal components. However, some discrete frequency components appeared when fuel composition was altered.

A very detailed study is conducted by Dowling [185] on combustion noise in which all relevant aspects of combustion are highlighted and analytically evaluated. This includes an explanation of the broadband nature of the direct combustion noise, rationality behind the appearance of indirect combustion noise, rumble noise, and combustion instabilities. The latter two kinds of phenomena are associated with the feedback of noise due to reflection from the combustor walls. The study is equally valid for understanding noise from the APU combustion process as it covers the level of noise for all ranges of mass flows. As an example, Fig. 7 shows the relationship between magnitudes of direct and indirect combustion noise as a function of Inlet Mach number (in the flame zone) and outlet Mach number (at combustor nozzle outlet). This relationship has been found using analytical studies which also revealed that indirect combustion noise is present at lower frequencies. Engine manufacturers can be commended in achieving a reduction of the indirect combustion noise, which has been the result of decreasing flow rates through the engines with the help of a high by-pass ratio design.

4.4.1. Discussion on APU noise experimentation

It is apparent from the literature survey that, with regards to the APU noise, efforts have been mainly made towards understanding noise generating sources and their attenuation. This is evident from the summary of experiments presented in Table 5. None of the activities have been targeted towards health monitoring and therefore no APU is subjected to failure(s) during acoustic data collection. Moreover, the number of instances where APU noise is measured in an acoustically treated room outnumber the occasions where experimentation is done on actual aircraft. Also, the literature is not rich with APU noise gathered very close to the whole engine, that too on the aircraft where all the associated systems are intact. Most importantly, the complete spectrum and directivity of noise have never been captured in the near-field and the results compared with any of the noise prediction models. The numerical simulations which have been performed focused on either performance analysis of external acoustic treatments or modeled a specific component of the complete system. In some of the cases, 1/3 Octave band results are presented which may be a requirement for certification purposes but in this representation, the accuracy of spectral content is lost due to low resolution. Similarly, the selected frequency span for analysis has been mostly a few kilohertz because of more interest in understanding the combustion process rather than the whole APU noise. Lastly, there is a dearth in understanding noise under unsteady/transient states that may help in diagnosing faults in components that control overall APU operation.

4.5. Engine noise of airborne platforms with novel architectures

Currently, all the conventional methods of engine noise reduction have been exhaustively studied, and, based on the envisaged requirements, novel techniques are needed to be explored. In Ref. [186], various options are discussed that have been explored for reducing noise from the aircraft including its engines. The study highlights the targets which have been set by ACARE 2020, FlightPath 2050, NASA's N+2 and N+3 goals. The target reduction in noise is set to be 50%, 65%, 42 EPNdB, and 71 EPNdB respectively. Noise reduction by using various configurations of a blended-wing-body aircraft is studied in Ref. [187]. It is found that, by using multiple engines, the jet noise frequencies would be high and would be greatly attenuated by atmospheric attenuation. Similarly, the silent aircraft design suppresses the forward radiating engine noise by mounting the engines above the airframe and extending the engine exhaust ducts with acoustic liners [188]. Distributed exhaust nozzle arrangement is yet another way of reducing jet noise by dividing the flow into very small exhaust plumes [189]. An open rotor design with counter-rotating propellers is also proposed to reduce the jet noise by the high bypass ratio design, however, there would be an increase in the sound radiated due to the interactions between the blades and the airflow [186]. Apart from the complexities involved with the manufacturing of aircraft with novel designs, it is highlighted that the noise reduction techniques employed by the concept aircraft have been theoretically tested, and they need to be validated with experimental data once the designs are practically realized.

As the VTOLs and air taxis are becoming a reality now, their utilization is likely to grow and noise would become a concerning factor [190]. Although the noise radiated by electric-powered VTOL is expected to be quite less as compared to helicopters [191], the number of air-taxis is likely to increase because of affordability. Therefore, it is prudent to design the aircraft for urban air mobility with low levels of noise. In this regard, various designs have been put forward keeping in view the performance, operational effectiveness, and noise emissions [192]. It is desired to have low rotor tip speeds so that the noise generated by the fan is minimum. Similarly, for reducing the noise generated due to the rotor-rotor interactions, the blade shape and spacing have to be optimized. The noise generated by the blade-vortex interactions is also annoying and can be controlled by adjusting the blade tip twist [193]. Out of the several designs for an air-taxi, the multi-rotor design is found to be the least noisy but has limited range and cruise speed [194].

5. Acoustics for fault diagnostics of aircraft auxiliary power unit

In the previous sections, all the necessary information has been covered in the subject domain. This assisted in understanding the research gaps, opportunities, and challenges involved in the field of acoustics-based fault diagnostics of an aircraft system like an auxiliary power unit.

5.1. Research gaps

Certain areas have been identified to be either in the state of infancy or not covered in the public domain literature. It is believed that, if these spheres of knowledge are explored extensively, it would contribute towards the development of a comprehensive fault diagnostic methodology using sound measurements. The gaps have been identified to be the following:

(a) Incomplete information about APU failure modes for legacy and state-of-the-art aircraft. This can be addressed by collecting information from the defect reports and the maintenance records.
(b) There is no information about the possible list of APU faults that can be diagnosed with the help of acoustics.
(c) Less information about the acoustic response of radial compressor and turbine is available as compared to their axial counterparts. Presently, literature provides noise prediction models for axial systems, but such models are unavailable for the radial/centrifugal category.
(d) The dearth of acoustic measurements in the vicinity of APUs under various operating and ambient conditions has also been observed from the literature. Such data can provide useful information about the distribution of sound energy around an APU. Furthermore, it may also indicate the systems which contribute towards the overall noise at closer ranges.
(e) The optimum number and location of microphones for gaining maximum information about an APU has also not been identified.
(f) No aircraft have been reported to have been instrumented with acoustic sensors with an aim to acquire sound data for APUs. Mostly, acoustic data has been acquired in test-cells and anechoic conditions. In an actual configuration, the effects of associated components (intake, exhaust muffler, enclosures, oil cooler, vibration isolators, bleed flow) will be visible.
(g) Effects of Environmental Control System, Main Engine operation, and wing anti-ice system noise on APU compartment noise have not been studied. This study is necessary to evaluate the stationarity of the acoustics signals inside the APU compartment under all conditions.
(h) Acoustic analyses have not been performed during startup/shutdown stages. It is believed that these signals carry useful information about the system state and can be used for diagnostics.
(i) Due to obvious reasons, APUs (in actual configuration) have never been subjected to single/multiple faults for data collections and onward development of fault diagnostics methodologies.
(j) The complete spectrum of APU noise has not been predicted using any of the noise prediction models and validated with actual aircraft data.
(k) A detailed set of acoustic features have not been explored for APU fault diagnostics. The features should be such that they produce

consistent results under all operating conditions and would be unaffected due to the transients and background noise.

(l) Optimum and robust fusion methods for APU fault diagnostics are also non-existent. A fusion of thermodynamic, vibration, and acoustics features may assist in the correct identification and classification of faults in a system.

(m) Casing-radiated noise from an APU is not studied in detail and they have neither been correlated with the thermodynamic parameters. Such type of noise will be prominent at closer ranges to the engine and is important to understand for fault diagnostics.

5.2. Opportunities

Acoustics have a tremendous amount of potential which has not been harnessed properly for gas turbine health monitoring. It is believed that, by acquiring knowledge about prominent sources of noise in gas turbines and using it for engine health monitoring, a better judgment could be made about the engine condition. In the field of fault diagnostics and engine health monitoring, acoustics may outperform other sensors due to the following reasons:

(a) Ability to capture a wide range of information about engine operation. From engine startup until its shutdown, important information can be acquired using microphones, which can be used for developing fault diagnostic mechanisms.
(b) Installation of acoustic sensors is convenient. Since they are non-intrusive in nature, the microphones can be placed at an appropriate location without interfering with the safety and integrity of a system.
(c) Acoustics can detect variation in the flow, which is not reported by vibration sensors.
(d) Acoustic sensors can capture higher frequencies (up to 20 kHz). The frequency response of vibration sensors is reduced if the adhesive is used for installation.
(e) Vibration from components translates into sound energy which can be acquired by the microphones. If the strength of these signals is high, they can be used to monitor key components of an engine like bearing and gears.

5.3. Challenges

Acoustics is inherently a complex field that poses several challenges while dealing with them. The difficulties associated with auxiliary power unit acoustics are:

(a) Effects of background noise are fairly pronounced and are difficult to control. Such noise may be generated by rotating or vibrating components present in the vicinity of the subject-under-test.
(b) Like vibration analysis, component details are needed to ascertain the characteristic frequencies of bearing and gears in acoustic signals. This information may be proprietary to the manufacturer and may not be available.
(c) Acoustics suffer from reflections from the surfaces resulting in multipath propagation effects. This leads to variation in sound signals if the environment is changing (due to aircraft motion, etc.).
(d) Accessibility to aircraft with functional APU and using the same for research purposes is also considered to be a challenge. Due to the same reason, little or no information is available on APU acoustics response on actual aircraft with all necessary systems intact.
(e) In order to accurately characterize acoustic response, unsteady pressure sensors are required which are intrusive in nature. Furthermore, the acoustic response is highly affected by thermodynamic parameters in and around the APU, therefore a complete picture of thermodynamic parameters is needed within and outside the APU for accurate modeling. Such a detailed level of instrumentation is not feasible on actual aircraft and has not been performed. Engines have normally been instrumented while being on the ground, that too independently on a test cell. On an actual aircraft, installation of such sensors is unfeasible and is, therefore, a challenge.

6. Summary

After carrying out a detailed literature survey of the areas mentioned in Fig. 1, the following represents a summary:

(a) Aircraft APUs are an important part of commercial aircraft and their operational readiness is paramount for airline activities. In legacy aircraft, where sensor coverage is limited, the operators resort to conventional maintenance practices. Therefore, scheduled maintenance can be carried out even if it is not needed. The APU controller (FADEC) performs basic diagnostics. For detailed fault analysis, manufacturers provide troubleshooting manuals. Traversing through the manual is generally a cumbersome process and may even require the removal of the APU from the aircraft for further scrutiny. A comprehensive view of the technical advancements made recently in APU design and requirements is also presented. As aircraft become more electric, APUs are also required to provide increased levels of power density efficiently and reliably (Section 2).
(b) Performance-based diagnostics is the classical way of assessing the cause of degradation in a gas turbine. The literature also suggests the fusion of information at various levels for robust results. Gas path analysis is a model-based approach and hence requires in-depth knowledge of system parameters, an approach that has been found to be productive when the engine is in steady-state. All types of turbomachinery have a gearbox and a set of bearings and the nature of their degradation is common. Therefore, there is a plethora of information in diagnosing such faults, especially using vibration analysis. The methods range from time-domain analysis to more complex signal processing techniques and even include machine learning approaches. Relatively more analysis has been done using test-rig data, which is generally not representative of a complete system. Furthermore, component specifications are a pre-requisite for any of the presented approaches. These specifications are important to compute the characteristic frequencies that indicate component degradation. In the absence of such specifications, it is difficult to isolate the frequency of interest in the presence of various undetermined sources. With the increasing demand for air travel, the next generation of aircraft will be high performance, efficient and reliable. This reliability can only be achieved if innovative fault diagnostic techniques are incorporated in the design during the initial phases of development (Section 3).
(c) Airborne sound has also been evaluated for machine diagnostics, but not as rigorously as its counterpart (vibrations). Results are shown to be reliable, however, experimentation is generally done inside an anechoic chamber using a subset of the whole system. This completely excludes measurements and analysis done on a complete system like APU. Moreover, due to the complex nature of acoustics, the developed schemes are data-driven with no support from the physics of sound (Sub-section 3.4).
(d) The study of sound from gas turbines and APUs has been of great interest to the research community. A huge amount of work has been done in instrumenting engines, acquiring far-field noise data, performing source separating techniques, and analyzing the effect of engine power on noise levels. Moreover, it is envisaged that the interest in acoustic measurements is likely to increase with the increase in Urban Air Mobility (Section 4).

(e) The last section of the review paper discusses the research gaps, opportunities, and challenges, of which there are many, involved in the field of fault diagnostics of aircraft APUs using sound measurements (Section 5).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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